M 2014

U. PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

STRATEGIES FOR THE MINIMIZATION OF THE BALANCING COSTS OF A VARIABLE RENEWABLE ENERGY PRODUCER

JOÃO SARAIVA DE CARVALHO MORAIS DE CASTRO
DISSERTAÇÃO DE MESTRADO APRESENTADA
À FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO EM
ENGENHARIA ELECTROTÉCNICA

U.PORTO
FEUP FACULDADE DE ENGENHARIA UNIVERSIDADE DO PORTO

MIEEC - MESTRADO INTEGRADO EM ENGENHARIA ELETROTÉCNICA E DE COMPUTADORES **2013/2014**

A Dissertação intitulada

"Strategies for the Minimization of the Balancing Costs of a Variable Renewable Energy Producer"

foi aprovada em provas realizadas em 18-07-2014

o júri

Presidente **Professor Doutor Vladimiro Henrique Barrosa Pinto de Miranda**
Professor Catedrático do Departamento de Engenharia Eletrotécnica e de Computadores da Faculdade de Engenharia da Universidade do Porto

Professor Doutor Pedro Manuel dos Santos Carvalho
Professor Associado do Departamento de Engenharia Electrotécnica e de Computadores do Instituto Superior Técnico da Universidade Técnica de Lisboa

Professor Doutor Manuel António Cerqueira da Costa Matos
Professor Catedrático do Departamento de Engenharia Eletrotécnica e de Computadores da Faculdade de Engenharia da Universidade do Porto

O autor declara que a presente dissertação (ou relatório de projeto) é da sua exclusiva autoria e foi escrita sem qualquer apoio externo não explicitamente autorizado. Os resultados, ideias, parágrafos, ou outros extratos tomados de ou inspirados em trabalhos de outros autores, e demais referências bibliográficas usadas, são corretamente citados.

João Castro

Autor - João Saraiva de Carvalho Morais de Castro

Faculdade de Engenharia da Universidade do Porto

Faculdade de Engenharia da Universidade do Porto

Strategies for the minimization of the balancing costs of a variable renewable energy producer

João Saraiva de Carvalho Morais de Castro

Final Version

Mestrado Integrado em Engenharia Electrotécnica e de Computadores
Major Energia

Supervisor: Prof. Manuel Matos
Second Supervisor: Dr. Vera Silva
Third Supervisor: Dr. Marianne Entem

June 2014

To improve is to change. To be perfect is to have changed often.

Winston Churchill

Abstract

The surge of deployment of variable renewable energy sources is being followed by an increase of imbalances, caused by this variable production. This leads to a growth in the necessity of reserves, to compensate these imbalances and ultimately to an increment on the cost and on the complexity of the operation of the electric system.

In addition to this, the Variable Generation Producer (VGP) is not always required to participate in the electricity markets and cover its imbalance costs. This situation, however, is likely to change in the near future: the VGP may have to become an active market participant.

As a result, a need for investment in tools and in the creation of strategies to minimise imbalance costs is created.

The current dissertation provides such a tool and assesses different bidding strategies for a VGP participating in short-term electrical markets today.

It starts by given insight on the French short-term electrical markets. It proceeds to characterize different forecasting tools of wind power production and of market prices, imperative to the success of the bidding strategies. The methodology based on a Monte Carlo simulation is also detailed using the current problem as an example. The work proceeds to depict the different strategies under analysis, which are applied to a study case based on the French electrical market. From the comparison of the different strategies, conclusions regarding the best course of actions of the VGP are drawn.

This dissertation presents a simpler approach to the optimal bidding problem in short-term electrical markets and analyses different bidding strategies for a French VGP. It also sets the basis for the application of such methodology to a different electrical system where VGP has a greater level of penetration.

Resumo

O crescente aumento da exploração de unidades de produção dispersa tem sido acompanhado por um aumento dos desvios criados por estas unidades. Tal leva a que haja uma necessidade incremental de reservas, de modo a compensar esses desvios entre produção e consumo. Em última análise, o custo e a complexidade de operação do sistema elétrico têm vindo a crescer nos últimos anos.

Por outro lado, os produtores de geração variável (PGV) não são obrigados a participar nos mercados de eletricidade, de modo a cobrirem os custos dos seus desvios de produção. Contudo, a tendência futura será para que esta situação mude e que passem a ser participantes ativos dos diversos mercados de curto tempo.

Assim, cria-se a necessidade de investir em ferramentas e de criar estratégias que permitam ao PGV minimizar os seus custos com os desvios que cria no sistema.

A presente dissertação pretende fornecer uma ferramenta que permita aplicar diferentes estratégias para as licitações de um PGV que participe nos diversos mercados de energia elétrica.

Para tal, começa por descrever os mercados franceses de curto termo. Depois, carateriza diferentes ferramentas de previsão de produção eólica e de preços de mercado, imprescindíveis ao sucesso das estratégias de licitação.

De seguida, apresenta-se a metodologia utilizada, que se baseia no Método de Monte Carlo. O qual é revisitado e exemplificado com o problema em mãos.

As diferentes estratégias são também apresentadas, aplicadas a um caso de estudo baseado no sistema elétrico francês e o seu desempenho é comparado. Dessa comparação são retiradas conclusões relativamente à melhor forma de um PGV participar nos diferentes mercados de eletricidade.

Os principais contributos desta dissertação são: fornecer uma abordagem simplificada ao problema das licitações ótimas nos mercados de curto termo de eletricidade e analisar diferentes estratégias para licitar nesses mesmos mercados. Este trabalho é passível de ser expandido de forma a simular outros mercados onde, nomeadamente, haja uma maior penetração de fontes de energia variáveis, o que possibilitará retirar conclusões sobre a evolução futura dos mercados de energia elétrica.

Acknowledgements

I would like to express my deepest gratitude to Dr. Vera Silva, whose determination and perseverance made this internship a reality and whose experience and expertise made it an excellent learning opportunity.

I also would like to thank my supervisor Dr. Marianne Entem, for her help in the understanding of the French electrical markets.

A word of appreciation and gratitude is also due to the people from OSIRIS at EDF. Especially to Clémence Alasseur, for all her diligent help with the spot price forecasting.

In addition to those, I would like to thank my supervisor at FEUP – Prof Manuel Matos – for all his support, advice and guidance throughout this project.

To Ricardo Bessa, whose aid at critical points in the development of this work was decisive.

At a personal level I would like to thank the people of R12 of EDF, who received me so well and integrated me in their working group.

To Nuno, thank you for joining me in this challenge and to Rita, Joana and Pedro, for making Paris my home for the last few months.

To my parents and family, their support during the best and the worst times was what made me go forward.

INESCPORTO®
INSTITUTO DE ENGENHARIA DE SISTEMAS
E COMPUTADORES DO PORTO

eDF

x

Contents

List of Figures

List of Tables

Abbreviations and Symbols

List of abbreviations

ARIMA	Autoregressive Integrated Moving Average
BRE	Balancing Responsible
BM	Balancing Mechanism
CDF	Cumulative Distribution Function
CRE	Comission de Régulation de L'Énergie
DA	Day-ahead Market
EDF	Electricité de France
ENTSO-E	European Network of Transmission System Operators for Electricity
FLF	Forecasted Load Factor
GARCH	Generalised Autorregressive Conditional Heteroskedasticity
GAMS	General Algebraic Modelling System
GLM	Generalised Linear Model
ID	Intraday Market
IS	Imbalance Settlement
LF	Load Factor
MAR	Minimum Assured Revenue
PCR	Primary Control Reserve
PDF	Probabilistic Density Function
RTE	Réseau de Transport d'Électricité
VaR	Value at Risk
VGP	Variable Generation Producer
SARIMA	Seasonal Autoregressive Integrated Moving Average
SCR	Secondary Control Reserve
STD	Standard Deviation
TCR	Tertiary Control Reserve
TSO	Transmission System Operator

List of symbols

PMP_b	*Prix Moyen Pondéré à la Baisse* is the weighted average price of down regulation
PMP_h	*Prix Moyen Pondéré à la Hausse* is the weighted average price of up regulation
F_π	Forecasted spot price curve
F_T	Initial spot price curve
β_v	Volatility parameter
a_v	Volatility parameter
$\mathcal{E}$	Normal distribution with zero mean and a standard deviation of one
T	Delivery time
t_0	Corresponding hour of the initial spot price curve
TP	True positive
FP	False positive
FN	False negative
L	Electrical Demand (load)
ΔL_{30min}	Variation of demand over a 30 minutes period
π_{IS}^{+}	Positive imbalance settlement price
π_{IS}^{-}	Negative imbalance settlement price
π_{DA}	Day-ahead spot price
π_{BM}^{Up}	Up regulation price
π_{BM}^{Down}	Down regulation price
$R(W_{DA}, W_{ID},)$	Revenues of the VGP
W	Bid wind power
W_{DA}	Day-ahead market bid
W_{ID}	Intraday market bid
π_{ID}	Intraday market price
Δ_{IS}^{+}	Positive imbalances
Δ_{IS}^{-}	Negative imbalances
$E(R)$	Expected value of $R(W_{DA}, W_{ID},)$
$\hat{E}(R)$	Estimation of the expected value of $R(W_{DA}, W_{ID},)$
$V(\hat{E}(R))$	Variance of $\hat{E}(R)$
$\sigma\left(\hat{E}(R)\right)$	Standard deviation of $\hat{E}(R)$

N	Number of scenarios used in the Monte Carlo Simulation
$V(E)$	Variance of the expected value of $R(W_{DA}, W_{ID},)$
$\hat{V}(R)$	Unbiased sample variance of $\hat{E}(R)$
β	Coefficient of variation
$CI(99\%)$	Confidence Interval of 99%
$V(W)$	Objective function of a VGP faced with a decision problem
$\hat{E}(W)$	Expected revenue of a VGP
W_R	Delivered wind power production
$\widehat{W}_{DA}$	Forecasted wind power production from day-ahead
$\widehat{W}_{ID}$	Forecasted wind power production during intraday
$\hat{\pi}_{IS}^{+}$	Forecasted positive imbalance settlement price
$\hat{\pi}_{IS}^{-}$	Forecasted negative imbalance settlement price
$[\widehat{W}_{DA}]_b$	Wind power bid on the day-ahead market
$[\widehat{W}_{ID}]_b$	Wind power bid on the intraday market
$\hat{\pi}_{DA}$	Forecasted day-ahead market price
$\hat{\pi}_{ID}$	Forecasted intraday market price

Chapter 1

Introduction

1.1 – Background

On March 2009, the European Union sowed the seeds for the proliferation of the deployment of variable renewable energy sources, by publishing the Directive 2009/28/EC [1]. It was determined, in said directive, that by 2020 20% of the electrical energy in Europe would be obtained from renewable sources. This and other policies that followed, together with changes in consumption patterns, profiles and predictability have been gradually shaping the European Power System into a new paradigm.

However, the three main objectives of these policies, sustainability, economic efficiency and security of supply may be opposed ones. As the installed capacity of variable generation sources grows, so do the imbalances caused by them, which leads to a greater necessity of reserves in order to maintain security levels.

The result is an increment in the costs and in the complexity of the exploration of the system, which creates a real hindrance to the implementation of the EU sustainability policies by creating economic inefficiency.

The Balancing Mechanism, responsible for compensating these imbalances, will therefore have a notorious impact on the market prices. The procurement of reserves and the provision of balancing energy to compensate the imbalances are eventually paid through the Imbalance Settlement Mechanism.

Market participants are always incited to provide accurate schedules of their production to the TSO and to participate in the provision of balancing services.

Variable Generation Producers (VGP), however, will be less incited to do so and instead to use bidding strategies in order to take into account all the uncertainties from prices and from production and, hence, position themselves in such a way that they could minimise their losses.

This is the motto of this dissertation: to minimise the costs of the imbalances caused by the VGP, by selecting a more favourable bid that makes account of the possible variations in both production and market prices.

1.2 – Motivation

Today, VGPs are not always required to participate in electricity markets and cover their imbalance costs, as there is little incentive to do so. In fact, it is the Balancing Responsible Entities (BRE) who financially settles the imbalance costs of the VGP. This is ought to change in the future, since VGPs are likely to be required to become active market participants. This creates a need for investment in tools and in the creation of strategies to minimise imbalance costs. The profits of a VGP will depend on day-ahead and intra-day market prices and impacted by their imbalance management strategies.

At the end of 2013, 20,7% of the electricity needs in France were met by renewable energy sources (including hydric generation) [2]. By 2020, the renewable energy sources should account for 23% of France’s energy mix, accordingly to the EU objectives set in the above mentioned Directive.

Since EDF is one of the 130 BRE in France, and with the perspective of growth of VG penetration, it is important for the company to assess the impact of different bidding strategies in the minimization of balancing costs, as well as to determine new price designs that would held the VGP accountable for its imbalances.

The motivation of this work is therefore to provide such an insight on the balancing mechanism in France, by assessing the costs of imbalances of the VGP; evaluate the impact of different bidding strategies in the imbalance costs and set the basis for further work with scenarios that include a higher level of VG penetration.

1.3 – Assumptions

In order to reduce the complexity of this work, but maintaining the acceptability of the conclusions, a set of assumptions are made.

Firstly, the minimization of the balancing costs is done indirectly by maximising the expected revenue from the participation in all of the considered markets. Another consideration regarding this matter is that the costs of participating in these markets are not considered, although it can effortlessly be included in the current methodology.

Secondly, only onshore wind power production will be considered, instead of all the renewable generation sources present in the French energy mix. The methodology can be adapted to include other types of VG, with reasonable ease.

Thirdly, the VGP and the BRE will be considered to be the same agent, in other words, it is the VGP that is held accountable for the imbalances he provokes in the system. Moreover, the VGP will aggregate all the onshore wind power production in France.

More technical considerations are also made: the VGP is a price taker in all the markets he participates. Since for the period considered the maximum penetration of wind power is merely 10%, the price taker assumption holds for the day-ahead market, as the impact of wind power is reduced.

For the intraday market, the influence of the VGP is acknowledge, but considered implicitly in the historical data used for the simulations.

As for the balancing mechanism, the influence of the VGP is initially neglected for matters of simulation, but taken under consideration when results are studied.

Considering, instead, that the VGP is in fact a price maker, would mean that the actions of all the other market participants involved would have to be accounted for, similarly to what is done on [3]. In addition to that, a more sophisticated price forecasting method that considers the wind power production would have to be implemented.

Another important assumption is that the intraday market has sufficient liquidity to enable all the necessary transactions for the VGP: all bids are accepted in the intraday market.

Due to the stochastic nature of the involved control variables, the different scenarios created are time-independent; a similar consideration was made in [4].

It is important to note that it was not an objective of the present work to create new forecasting tools. Thereby, the majority of the forecasting tools implemented were provided by EDF, from other projects. There was, however, an exception: the forecast of the imbalance settlement prices was created accordingly to the existing literature [5] [6].

Finally, during the intraday market, i.e. for hour-ahead forecasts, the VGP uses new information he collects from its wind power parks to enhance the meteorological forecasts provided by the TSO. This data includes local meteorological measurements, turbine outages and scheduled turbine maintenances. By doing so, every hour he has a better view of what might be its production for the following hour.

1.4 – Document structure

The present work is structured as follows:

Chapter 2: A brief analysis of the state of the art in this projects area of study is made. This also includes some of the forecasting methods tested.

Chapter 3: The mechanics of the French electricity market are explained, in order to have a better view of the decision times and possible actions used in the different strategies.

Chapter 4: The forecasting tools for wind power generation and for market prices that were used are detailed. These also include a tool for predicting the direction of regulation that the system would need.

Chapter 5: In this chapter the Monte Carlo Method is revisited, the methodology is depicted and the different strategies are presented.

Chapter 6: The case study on the French system; the data available and the main results are presented.

Chapter 7: The conclusions of this work are summarised in this chapter and also some suggestions of future work are made.

This document concludes with the glossary and the bibliography.

Chapter 2

Previous Work

Optimal bidding in short-term markets has been the focus of many studies. A review on the state of the art was carried out and the main conclusions are presented below.

In previous works, it has been assessed market behaviour and comparisons between different market designs in Europe were made [7] [8]. Others concentrated in the day-ahead market and evaluated different strategies with different risk attitudes [9] [10]; strategies that involved the participation in different markets from day ahead to balancing [4] [7] [8] or only day-ahead and intraday [11] or simply a single strategy that aimed at maximising the expected utility [10] [12] [3].

To do so, different formulations were used: [4] [7] [8] solves a stochastic optimization model that maximises profits using GAMS on CPLEX, under 1000 scenarios created from probable values of the variables at play.

In [12] an optimal quantile strategy was implemented as a stochastic optimization problem. The aim was to select the quantile that would not be penalised by the regulating market, even if a great imbalance would have to be made. This approach disregarded risk, so the authors decided to constraint the final solution in the decision space (setting the bids around the wind power point forecast) and later in the probabilistic space (setting the bid around the volume of the cumulative distribution at the point forecast).

On the other hand, a more complex approach was undertaken in [3] in order to consider the VGP a price maker in the Regulating Market. In fact all the above mentioned studies have considered the VGP a price taker in all the markets he participates, claiming that he did not have enough size in order to create an impact on volumes and prices traded.

The consideration of the price maker hypothesis led to a significant increment in the complexity of [3] when compared to works on similar subjects.

The authors formulated the problem as a bi-level optimization scheme that corresponds to a stochastic formulation of a Mathematical Program with Equilibrium Constraints, and cast as a Mixed-Integer Linear Program. The problem was later solved using standard optimization software.

Another standard approach is to consider that both wind power and price uncertainty are independent [4] [7] [8] and so are inter-temporal decisions [9] [12].

2.1 – Wind power forecasting

As shown by [10], forecasting of wind power production is key in order to better guiding the trading decisions. In his work Kernel Density estimation is carried out. This kind of non-parametric way of estimating probability density functions makes inferences on the population studied and, therefore is able to create smoother PDFs. Throughout the present work, when it would be necessary to compute either PDFs or cumulative density functions, Kernel Density estimation was used.

In [11], the author opts to use wind speed and direction measurements and Hirlam Numerical Weather Predictors in order to create a statistical model using power curve modeling. This model is later updated with refreshed information, so it can be used in the intraday market. In a previous work [9], the same author used a similar model to produce hourly probabilistic density functions of wind power production. Statistical tools were also used in [12] and a beta distribution in [3]. In [4] [7] [8] wind power was predicted using meteorological forecasts.

As mentioned in the previous Chapter, forecasting was merely a necessary mean in the development of this project. Hence wind power production forecasting was carried out using an existing tool in EDF [13].

In his study, the author considered different sources of uncertainty in the generation of electrical power: unit outages from conventional power plants and forecasting errors from variable generation. These, together with the result from the unit commitment of hydro and thermal power plants, were convolved and a probability density function of the surplus[1] of generation was computed. Given a certain risk-level, both upward and downward regulation reserves would be obtained.

The tool, as a whole, is used in Section 4.4.1 of Chapter 4 to determine the most probable direction in which the system is in need of regulation.

However, the module of wind power production was adapted to serve the purposes of the present work.

---

[1] The generation surplus was calculated from the difference between the realised and the forecasted power balance.

The *Matlab* tool created during the development of [13] combines historical data of wind power and point forecasts of wind power load factors to create hourly PDFs of wind power uncertainty. This is done for 24 hours before delivery, i.e. for day-ahead market participation. For the intraday market a similar method is used but instead of historical forecast errors, a persistence technique is used and it is assumed that the errors that occurred in one hour are the same for the following hour.

Further details on this method can be found in Section 4.1 and the interested reader could also be directed to [14] for a complete study on the state of the art of wind power forecasts.

2.2 - Day-ahead spot prices forecasting

In his papers [4] [7] [8], Chaves treats day-ahead prices as time series and uses SARIMA and then GARCH on the residual errors, to make predictions on these prices.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) is used to understand the data and make predictions of future occurrences of the day-ahead prices, which show a seasonal pattern. Two polynomial functions, one related to autoregression and another to the moving average, are used to modulate the time series. The denomination “Integrated” is related to an initial differencing step that can be applied to remove the non-stationarity of the time series.

The GARCH model is a generalization of the Autoregressive Conditional Heteroskedasticity[2] model. Like the SARIMA, it is also used to analyse time series and in the case of [4] [7] [8], to analyse the errors resulting from the application of the SARIMA model. This model is often used when there is reason to believe that the error has a characteristic variance.

In [10] prices are assumed to be Gaussian and are modeled using historical data of the variance, mean and the correlation from each individual hour of the next day. Weekdays and weekend days are treated separately. In [12] [3] the author follows the same approach of [5]: a semi-parametric approach that uses quantile regression.

A different approach was undertaken, for the same reasons mentioned above for wind power forecasting: a Gaussian multi-factor price model used at EDF for forecasting forward prices, was adapted for the purpose of this study to become a forecasting tool.

The basic principle of this method is to simulate volatility, using Brownian Movements, around an already known spot prices curve. Several possible values for the day-ahead price, which are computed into a PDF, by means of Kernel Density Estimators, result from this method.

---

[2] In statistics, heteroskedasticity is the characteristic of a population where sub-groups show different variances.

In the end of the process it is possible to obtain a distribution of possible realizations of the day-ahead price, in which for any given hour the expected price is the same that occurred for the corresponding hour of the initial curve.

The interested reader could also be directed to [15] for a complete review on the state of the art on electricity spot price forecasting.

2.3 - Intraday prices forecasting

The intraday price, because it results from a *pay as bid* auction, is not known. In [4] [7] [8] the weighted average of the intraday prices is considered to be the price activated for a specific hour. The author then proceeds to make his predictions with the same approach used for spot prices (SARIMA and GARCH modeling).

In [11] the intraday price was modeled as a triangular distribution, using the minimum, maximum and average intraday prices, published by the market operator. From this distribution a cumulative one was created in order to assess whether or not the price would be accepted. This would simulate intraday market liquidity, which tends to be low, as the majority of market participants – which are conventional generation producers – prefer to make their trades in the day-ahead market. The intraday is mainly use to trade electric power from variable sources or for producers with conventional generation to trade after an unexpected outage took place.

Initially it was considered to predict intraday prices in a similar fashion of [11], but using fuzzy sets instead of probability distributions. This path was abandoned due to the fact that once fuzzy sets were used all the results obtained would have to be calculated as fuzzy numbers.

A second approach studied was to use a uniform distribution of the prices, but, as further detailed in Chapter 4, it was finally decided to forecast intraday prices using the same method implemented for the day-ahead price, due to the strict relation between day-ahead and intraday prices as seen in [16].

2.4 - Imbalance settlement prices forecasting

The prices applied in the imbalance settlement are greatly dependent on the prices seen on the balancing market, so forecasting these will help forecasting those.

In [4] [7] [8] it was not necessary to make forecasts, as prices are published, together with the direction of the regulation, close to real time. This hugely improves the performance of any of the strategies used in markets with such a scheme, as it allows the VGP to avoid penalties. In fact, and as it is seen in [9], the importance of anticipating the balancing prices is such, that errors in these predictions will completely make any strategy irrelevant.

These prices are forecasted in two distinct ways: in [9] and in [11] the simulation is run using perfect knowledge of the imbalance settlement prices, using a naïve prediction that takes the values seen on the previous month and the average value of prices of the previous year are tested. A different approach is made in [12] [3] as the approach of [5] is used. As the system's deviation is necessary for making these forecasts under the methodology of [5], the author opted to use a Student t-distribution in [3] to make such predictions on the most likely direction of regulation.

While in [4] [7] [8] the author included the imbalance costs in the optimization function, in [9] these were simulated in a different manner. Imbalance settlement rules were adapted to a loss function that would give the estimation of the economic loss or regret associated to each bid. This function was then taken as a transfer function that would create a loss forecast based on wind power forecasts and bid alternatives.

A similar approach was later used in [11], but now the imbalances were modeled as a penalty function of the intraday bid and prices.

Because a different system was studied (in the US) in [10] a different penalty scheme was simulated.

In [4] Dutch balancing rules were applied. In this system a dual marginal price is used in order to limit arbitrage and hold the VGPs accountable for their imbalances.[3] Despite simulating such a market, the fact that in 90% of the cases there was only one direction of regulation and also the fact that imbalances were not very high, the market behaved as having a single price throughout the simulation.

A similar dual marginal price system is implemented in Denmark and was studied in [9], [11] and in [12]. In [3] a single price is explicitly used.

Since the French market has a dual price system, the approach implemented is based on the work of [5].

In his thesis, the author starts by extracting the spot price component of the imbalance settlement price. Hence, it is obtained two different prices: a positive and a negative one. Those prices represent the upward and the downward regulation prices, respectively. Therefore, the upward regulation price occurs when the system is in need of upward regulation and the same goes for the downward regulation prices. Thus, prices are forecasted separately and their forecast is dependent on the result of the forecasting of the regulation direction.

As a result, the forecasting of the imbalance settlement prices is made in three phases: firstly, it is necessary to make predictions regarding the direction of regulation the system is going to need; then the upward and the downward regulation prices are forecasted,

[3] In France a similar dual pricing system is implemented, but these prices are not marginal, they are in fact the weighted average of the accepted offers for up and for down regulation, as it will be explained in Chapter 3.

depending on the previous results; in the end of the process, the regulation prices are added to the spot price and the imbalance settlement prices are finally obtained.

2.4.1 – Regulation direction forecasting

The regulation direction was also forecasted in [6]. To do so, the author implemented and tested four different methods: a generalised linear model (GLM), a Naïve Bayes classifier, a multilayer perceptron neuronal network and Support Vector Machines (SVM).

The first two are statistical models and the others are based on computational intelligence. The GLM is based on the usual linear regression method but allows the use of variables that have a distribution of errors different from the normal one. The Naïve Bayes classifier is further detailed on Chapter 4 and it applies the Bayes theorem with independency assumptions between the explanatory variables.

Neuronal networks and SVM are trained to analyse data, recognise patterns and make predictions based on these. The two are not probabilistic methods, thus given a set of explanatory variables, both models will either categorise the variables as being in one category or the other.

The above-mentioned methods can be applied as classifiers and, based on the values of a set of explanatory variables, the regulation the system is in need of can be predicted as being in the upward direction, downward direction or even that no regulation is necessary.

In [5] the author also implements SVM and, in addition to this, tests logistic regression. The latter method models the probabilities of a set of explanatory variables belonging to a given category, using a logistic function.

In the present work, both logistic regression and the Naïve Bayes were tested and the Naïve Bayes proved to be the method that provided the best results.

2.4.2 – Regulation prices forecasting

Upward and downward regulation prices are forecasted in [5] using quantile regression. This regression method is used to make predictions of quantiles of the response variable, accordingly to the values of the explanatory variables.

A similar method was implemented in this work, as it will be further elaborated in Chapter 4.

As mentioned before, once the regulation prices were obtained, it was just a matter of reconstituting the imbalance settlement prices, by adding the spot price.

As a result, the forecasting of the imbalance settlement prices is dependent on the accuracy of the predictions of the regulation direction, the accuracy of the regulation prices forecast and the accuracy of the spot price forecast, when predictions are made in day-ahead and the real spot price is yet to be known.

Chapter 3

The French Electrical Market

2.5 – An overview

Electricity is widely sold as a commodity product, but one must not forget that this good has distinct intrinsic characteristics.

Firstly, it is not easily storable in a large scale[4], therefore, the amount of electric power that is produced must equal, at all times, the amount of power that is demanded by consumers and the amount that is lost through production, transmission and distribution. When this condition is not met, the frequency of the system deviates from its set value. This can cause malfunctioning of electrical equipment and in extreme cases the disconnection of generation units and eventually a blackout.

Secondly, there is a significant level of uncertainty related to the amount of power delivered, as unexpected faults and outages might occur. In addition to those, the electricity produced from variable renewable sources is highly dependent on meteorological phenomena, which are not controllable.

Thirdly, electric power must be traded in real time by a sole market participant – the TSO – due to its physical characteristics.

As a result, there are several different electricity markets in which electric power can be traded from years in advance to a couple of seconds: forward, day-ahead, intraday and real-time markets. A brief explanation of the market mentioned before will follow.

On the forward market, financial trading can be made through the establishment of bilateral contracts or through stock exchange, from years before the delivery date until several weeks.

---

[4] Storage used to be widely done indirectly, by using pumped-storage hydroelectricity or flywheels, for instance. But in recent years, efforts on research have been made to find new and more efficient ways to store electricity.

The day-ahead market occurs the previous day and closes at 12 p.m. Electricity is traded in a spot market and paid by the price of the last accepted offer.

In the intraday, market participants can change their offers from the day-ahead market, by trading from 15 p.m. of the day before delivery, until one hour before delivery. The main goal of this market is purely economical.

During the balancing mechanism, which happens from one hour to 10 minutes before delivery, the TSO ensures that the reserves used to maintain the production/consumption equilibrium are re-established. This is done by calling for upward or downward regulation offers from the Balancing Services Providers (BSP). For an upward regulation, BSPs will make offers to increase their production or to decrease their consumption. If accepted, they are paid the price they propose. For a downward regulation, the BSPs pay the TSO for reducing their production or to increase their consumption. The TSO calls upon the most economic offers of Tertiary Capacity Reserves (TCR), as he is the sole buyer of this market. The trading is carried out in a *pay-as-bid* auction. The priorities in this market are both security and economic efficiency.

Lastly, although not being a market, in real-time (from several minutes until one second before delivery) the Primary Capacity Reserves is used for the Primary Frequency Regulation. This local automatic control system is sensible to variations in the frequency, resulting from situations when the injection of power is not equal to the withdrawals. When activated it either injects more power or reduces the power being injected in order to stabilise frequency variations. Once the PCR is being used, the Secondary Capacity Reserves (SCR) are automatically activated in order to replace the need for PCR and to restore the frequency to its nominal value. When necessary, the Tertiary Capacity Reserves (TCR) are manually activated in order to restore the SCR, to manage possible congestions and to bring the frequency to its nominal value if the SCR was insufficient. The TCR is traded in the following balancing market or is contracted between the BSP and the TSO. The main purpose of this mechanism is ensuring the security of the system. Figure 3.1 illustrates the different electricity markets on a timeline.

Since electricity is only physically traded in real-time, one will notice that the forward, the day-ahead and the intraday are in truth “forward markets” that trade a derivative product that matures in real-time. As a result, the signal conveyed by the balancing mechanism is of the utmost importance, as the Imbalance Settlement (IS) prices, which are a consequence of this market, will ultimately have a strong impact on the decisions of the market participant at the forward stage.

In addition to this, the different markets were created in a way that prevents the existence of any possible arbitrage between them. This fact was crucial in the forecasting of intraday prices, as it will be further explained in Chapter 4.

As it was alluded in Chapter 1, it is during the IS that the reserves used to counter-act the imbalances are levied. In France, it is the Balancing Responsible Entity (BRE), the market participant that financially compensates the TSO for the imbalances of the VGP. He will pay an Imbalance Settlement price when the VGP has produced less than what he has sold and he will be compensated every time the VGP produces more than what he has sold.

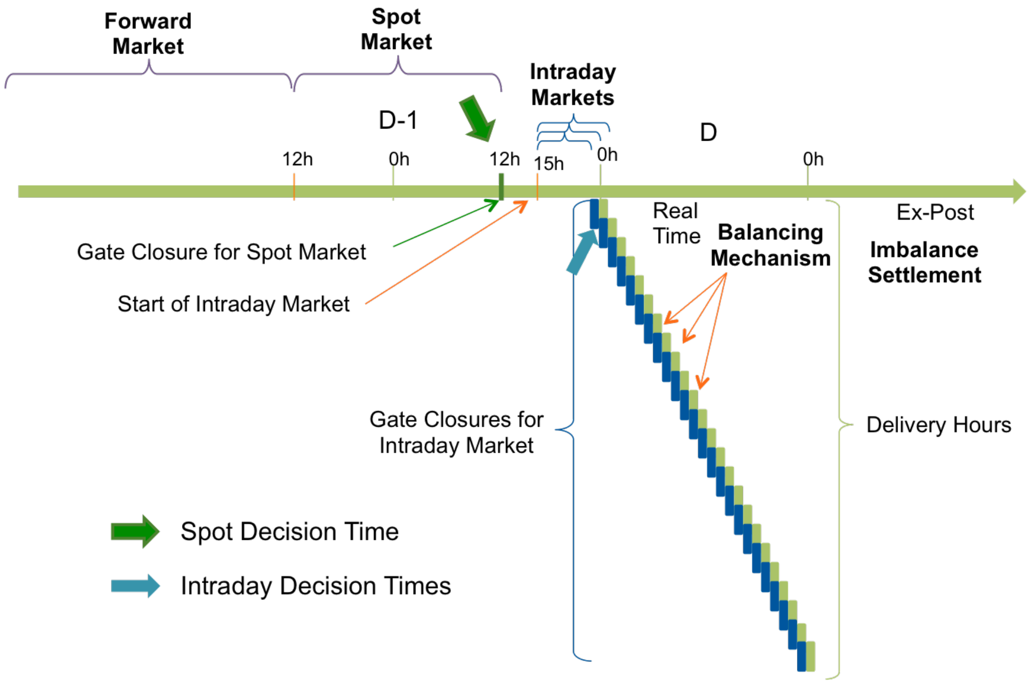

Figure 3.1 - Chronological representation of the various electrical markets in France

Since not all generation units are flexible enough to change their production scheduling in real time, or react with the necessary speed, regulation prices tend to be higher as time gets closer to the delivery instant. In addition to this, what is sold in the BM is not pure energy, there is also a flexibility component that must be considered and valued.

In brief, the revenue the VGP will obtain by participating in all the markets will not just depend on its profits from forward, day-ahead and intraday markets, but also by its costs with the IS. As it was mentioned in Chapter 1, this project was focused on maximising all the VGP's profits and not just minimising its costs.

Since the high levels of uncertainty characteristic of wind power production urge for the greatest amount of information possible and which are provided as one steps closer to the moment of delivery, this study was carried out focusing essentially on the markets that are closer to delivery time.

Those markets are the balancing mechanism, the intraday and also the day-ahead, since this is the one that provides more liquidity, allowing greater quantities of electric power to be traded. The reason for the liquidity of the day-ahead market is due to the fact that the majority of producers prefer to trade in day-ahead, in order to plan the production of their units and consider start-up costs.

2.6 - The different markets under analysis

2.6.1 - The day-ahead market

Energy can be traded through bilateral contracts or negotiated in a spot market for the 24 hours of the following day. The French market, being coupled with the German, the Dutch and the Belgium markets, integrates the CWE (Central Western European Market Coupling) and is overseen by EpexSpot. After gate closure (12 p.m.), the spot price for the following day, the volumes traded and the used interconnection capacities are published.

In the spot market, each market participant sends the market operator its price/volume selling offers and buying bids. Offers are ordered from the cheapest to the most expensive and bids in the reverse order from the highest paying to the lowest. The market operator will then maximise the social welfare function, accordingly to the available interconnection capacities. The resulting spot price will be the highest accepted price. Figure 3.2 illustrates the demand and supply aggregated curves, the spot price and the volume traded for the French day-ahead market. These aggregated curves refer to all the offers and bids made in this particular day and not to a single hour.

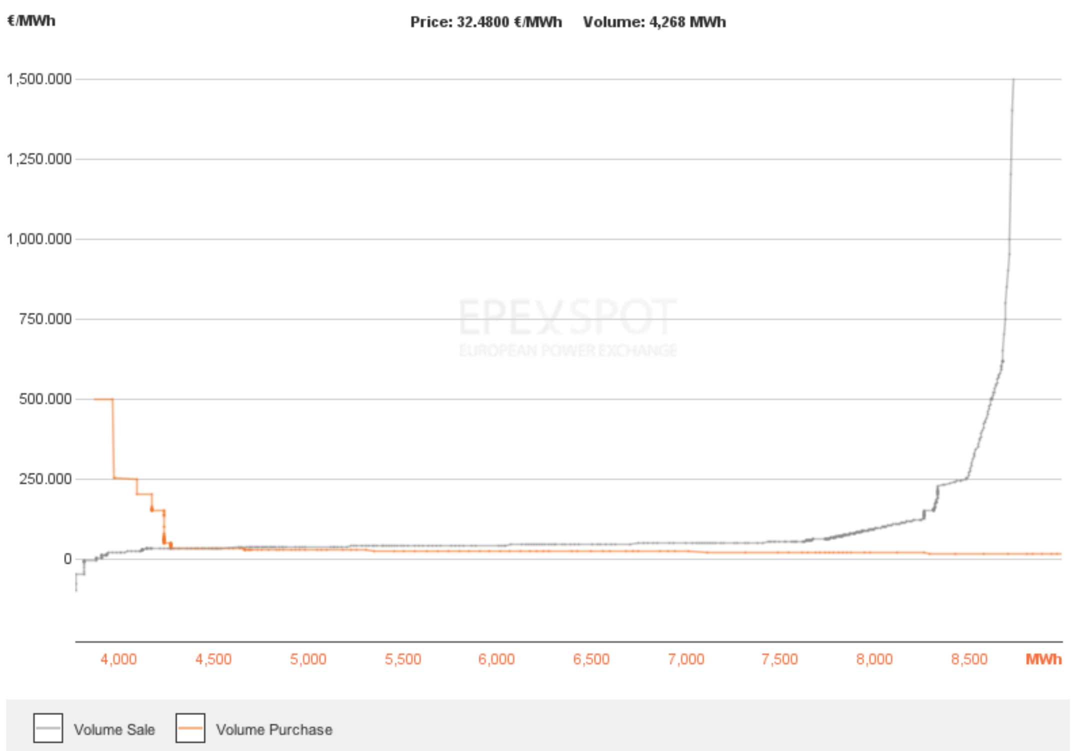

Figure 3.2 – Aggregated electricity demand and supply curves for the 27/01/14 in France [22]

Being a price taker, the VGP will make offers only in terms of quantities and with a zero price. Subsequently, its offers will always be accepted in this market.

The focus of this work is to assess different strategies for a VGP, when participating in short-term markets. Such strategies consist, not just in defining in which markets the VGP will participate, but also in determining the volume of electrical power offered by the VGP. The day-ahead market has a great importance for the VGP, as it will allow it to trade almost all of his expected production, due to the high level of liquidity of this market. All the strategies analysed involved the participation on this market either with an optimised offer or with an offer of the expected production.

2.6.2 - The production scheduling

Although not being a market, this is a crucial step between the day-ahead and the intraday markets, as vital information for the following markets is published: production programs of the thermal and hydro power plants; technical restrictions of each unit; the capacities defined for the PCR and for the SCR; forecast of losses and the curtailment programs. Together with these, information related to the BM is also made public: price offers for up and down regulation; the maximum and minimum power and energy requested, as well as the minimum duration of the activation of the regulation.

With this information, the TSO verifies the equilibrium between production and demand and calculates the necessary margins. If necessary he calls for new offers for up and down margins. These results are published at 21 p.m. of the previous day.

2.6.3 - The intraday market

On the intraday market, energy can be traded from 15 p.m. of the previous day until one hour before delivery (there must be a one hour neutralization delay) or in hourly blocs for the 24 hours of the current day. The French intraday market is also coupled with the German/Austrian and the Swiss markets and is overseen by EpexSpot. It is also possible to trade energy through bilateral contracts or on markets not coupled with the EpexSpot platform.

The following information is published after gate closure: prices and volumes traded; minimum, maximum, weighted average and last accepted prices.

Quotation is made continuously in this market and trading is made in a *first come first served* basis: as soon as there is a match between offer and demand a bilateral transaction is established. This exchange mechanism is known as *paid as bid auction*. As a result, the prices at which energy was traded are dependent on each specific auction and cannot be reconstructed for simulation purposes.

Prices are defined by the market participants and can legally range from -9999 to 9999 €/MWh. However market forces will act in order to keep this price as close as possible to the spot. As a result, arbitrage between the two consecutive markets becomes scarce. The following Figure illustrates the deviation of the intraday prices in 2012 from the spot prices:

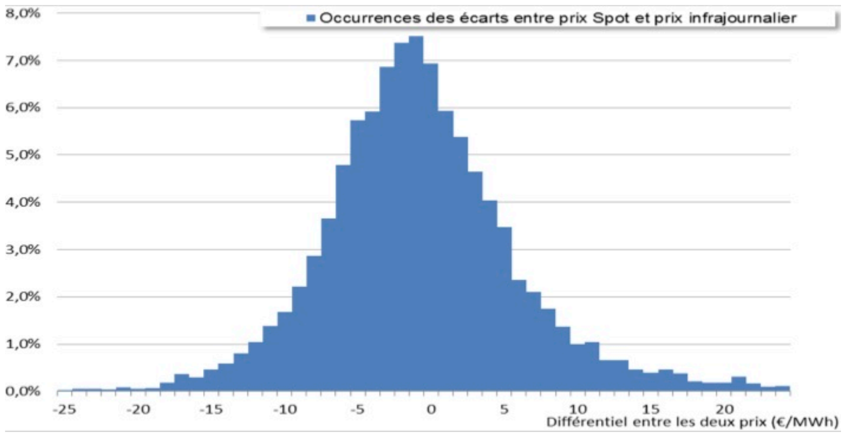

Figure 3.3 - Deviations between the French intraday and spot prices in 2012 [16]

As it can be seen, the difference between the intraday and the spot prices seems to follow a Gaussian distribution not exactly centred. This result will be extremely used in the forecasting of intraday prices, further detailed in the following Chapter.

The intraday market also has a tremendous importance for a VGP as it consists in the last opportunity to change its day-ahead offers, in order to be as close as possible to the actual delivered power. Trading in this market is virtually non-penalising for the VGP, but it has less liquidity, which means that not all the offers and bids of the VGP may be accepted. As previously mentioned, this market will be considered to have the necessary liquidity to allow all the VGP’s offers and bids to be accepted.

Some of the strategies studied include the participation in the intraday market, therefore conclusions regarding the advantages and disadvantages of the participation on this market will be drawned.

2.6.4 - The balancing mechanism

Because changes in demand and on production are always happening, the equilibria is maintained by automatic systems installed in the generation units. Those are the PCR and the SCR, a brief description of these two mechanisms can be found at the end of this document under the section Glossary.

Yet, these two reserves might not be sufficient, especially when a generation unit is lost or there is a fault in the system. That is why there also exists a TCR, which consists in asking the market participants for offers to change their production schedules in the intraday market. The role of the Balancing Mechanism is to manage these offers in an economically efficient way that maintains security standards.

The TSO will publish, one hour after delivery, the direction in which the regulation was needed: up, if the system was short and more production/less demand was needed or down, if the system was long and less production/more demand was needed. The price at which the regulation was paid is also published, and so are the volumes of energy requested and the imbalance settlement prices, which are consolidated three months after.

2.6.5 - The imbalance settlement

It is the Balancing Responsible Entity that will financially compensate the TSO for the imbalances caused by the VGP. Such imbalances are calculated in the influence perimeter of the BRE from the measured energy injections and withdrawals.

The following Table establishes the prices paid and received by the BRE:

Table 3.1 - Imbalance Settlement Price formation

Regulation Direction / VG Imbalance	**Up Regulation** (System Short)	**Down Regulation** (System Long)
Positive VG is long **VG is payed**	**Spot Price**	$\left[\frac{PMP_b}{(1+k)}; \textbf{Spot Price}\right]_{\min}$
Negative VG is short **VG pays**	$[PMP_h(1+k); \textbf{Spot Price}]_{Max}$	**Spot Price**

After the BM, a reference price is calculated from the weighted average prices of the accepted offers for up (PMP_h) and for down (PMP_b) regulation. These prices, or the spot price, will be the actual IS price: if, on one hand, the VGP has an imbalance in the opposite direction of the regulation the system requires, he will be penalise for its imbalance and will either receive less than the spot price or pay more than the spot price. If, on the other hand, its imbalance is helping the system, he will not be penalised (nor compensated as there is no arbitrage) and he will pay or receive the spot price, as if he had made its transaction on the day-ahead market.

As it can be seen, the French IS has a dual price design. The purpose of such price scheme is to prevent arbitrage between the spot and real-time markets: the producer always pays the costs of the imbalances he causes to the system, as it is seen in [8].

A coefficient *k*[5] is also included in order to incite market participants to reduce themselves their imbalances and not wait for the TSO to do so.

[5] Since 01/07/2011 k = 0,08

Chapter 4

Forecasts and Predictions

As it will be further explained in the following Chapter, the Monte Carlo simulation involves the creation of different scenarios. These are randomly generated from the universe of possible values of the variables at play.

In order to do so, point forecasts of these variables (for reference: wind power, spot prices, intraday prices and imbalance settlement prices) are not sufficient.

Probabilistic forecasted are needed in order to make the necessary draws to set up the different scenarios. The different probabilistic forecasting methods used are described in this Chapter.

4.1 - Wind power forecasting

Wind power is forecasted using a forecasting method implemented in a previous work at EDF [13]. This tool is re-calibrated with recent data and is adapted[6] in order to provide a probabilistic distribution of the possible values of wind power.

The method, fully described in [13], calculates wind power uncertainty for the 24 hours of the following day or for the next hour – fact that is exploited for the participation of the VGP in both day-ahead and intraday markets.

Day-ahead forecasts are computed using forecasted load factors and the installed capacity of wind power production and also the hour of the day of delivery. The previous study concludes that these were the variables that greatly influenced the standard deviation

[6] The adaptation was carried out since the application was developed in order to compute PDFs of wind power.

of wind power forecast errors and also the shape of the probabilistic distribution of such errors.

In fact, there is a strong relation between the STD and both forecasted load factors and the time distance: the further the delivery time, the more uncertain the forecast is, as it can be seen in Figure 4.1:

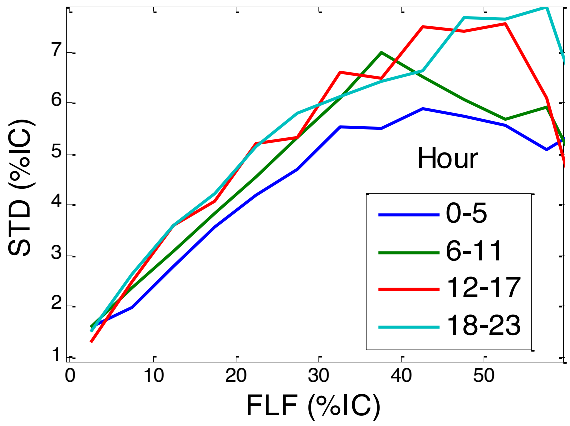

Figure 4.1 - The dependency of the standard deviation of the errors (STD) on time distance and on forecasted load factors (FLF) [13]

The shape of the distribution, on the other hand depends solely on the forecasted load factor: under-estimates are made with high load factors and over-estimates are made with low load factors.

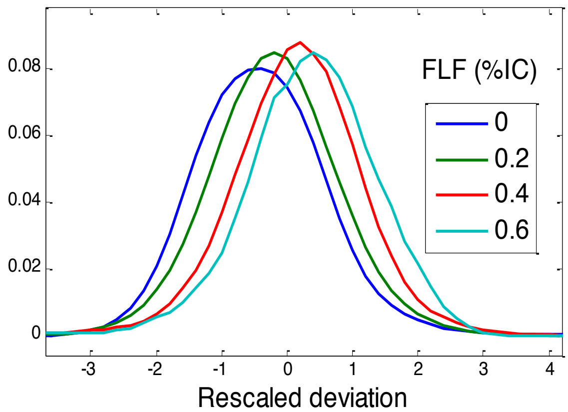

Figure 4.2 - The dependency of the shape of the distribution of the errors on the FLF. The deviation was rescaled to have a STD of 1, in order to better make the comparisons between diferente curves.

Using the above-mentioned explainable variables, PDFs of the distribution of errors are later computed using Kernel Density Estimators.

For the intraday forecasts, the same variables are used, except the hour of the day, since no time dependency is detected. Another important note is that forecast errors are not available hourly, as forecasts are not made with such frequency. The author opts to use a persistence technique[7] to forecast these errors.

Using the methodology described with the necessary data, PDFs of the wind power uncertainty are calculated and then re-scaled in order to provide uncertainties expressed in MW. To these distributions, with zero-mean, the point forecast - the product between installed capacity and the forecasted load factor - is added.

The final result is a curve with a similar shape as the one in Figure 4.3:

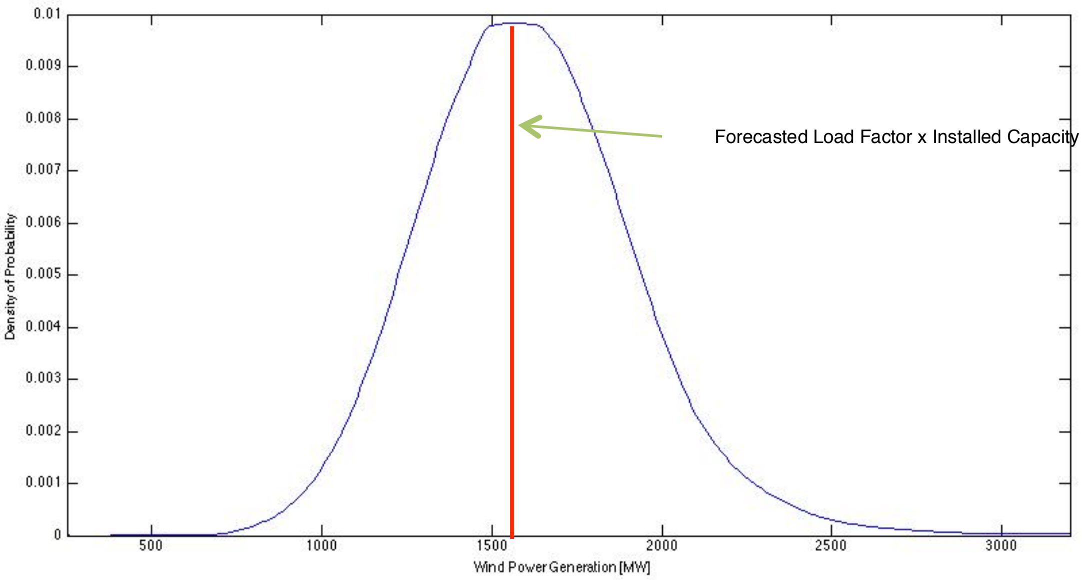

Figure 4.3 – Wind power production probabilistic forecast for 01/12/13 (0h)

4.2 - Spot prices forecasting

Spot prices are forecasted using an existing tool at EDF provided by the Optimization, SImulation, RIsk and Statistics Department (OSIRIS) [17]. This model is a more elegant way of simulating the spot price of the following day: starting with an already known spot prices curve, some volatility is created using Brownian Movements in order to simulate the possible deviations the spot price could suffer. This is carried out using [17]:

$$F_\pi(T) = F_T(t_0)e^{-\frac{1}{2}\beta_v{}^2\frac{e^{-2a_v(T-t_0)}}{2a_v}+\beta_v\sqrt{\frac{e^{-2a_v(T-t_0)}}{2a_v}}\,\mathcal{E}}, \qquad (4.1)$$

where β_v and a_v are volatility parameters calibrated for a specific market and $\mathcal{E}$ is a normal distribution. T is the delivery time and t_0 the corresponding hour of the initial curve. This time difference corresponds to 24h, since we are forecasting for all the hours of the

[7] The forecasted value is equal to the current observation.

following day, but this time lag has to be expressed in years (0.00274 years). $F_{\pi}(T)$ is the spot price curve that is going to be forecasted using the initial curve $F_T(t_0)$.

A closer look to the previous expression suggests that this volatility would be greater for the first hours and then reduced for the more distant ones. This is done in order to simulate what happens in reality: the volatility is greater as maturity time approaches. Another important fact that is implicit is that this model is created having in mind the strong mean reversion of spot prices that imposes great variations in prices to be merely spikes.

The initial curve and the volatility created around it are then used to build a smooth cumulative distribution function using Kernel Density. The reason for this will be fully detailed in Chapter 5 where a thorough explanation of the simulation carried out is presented.

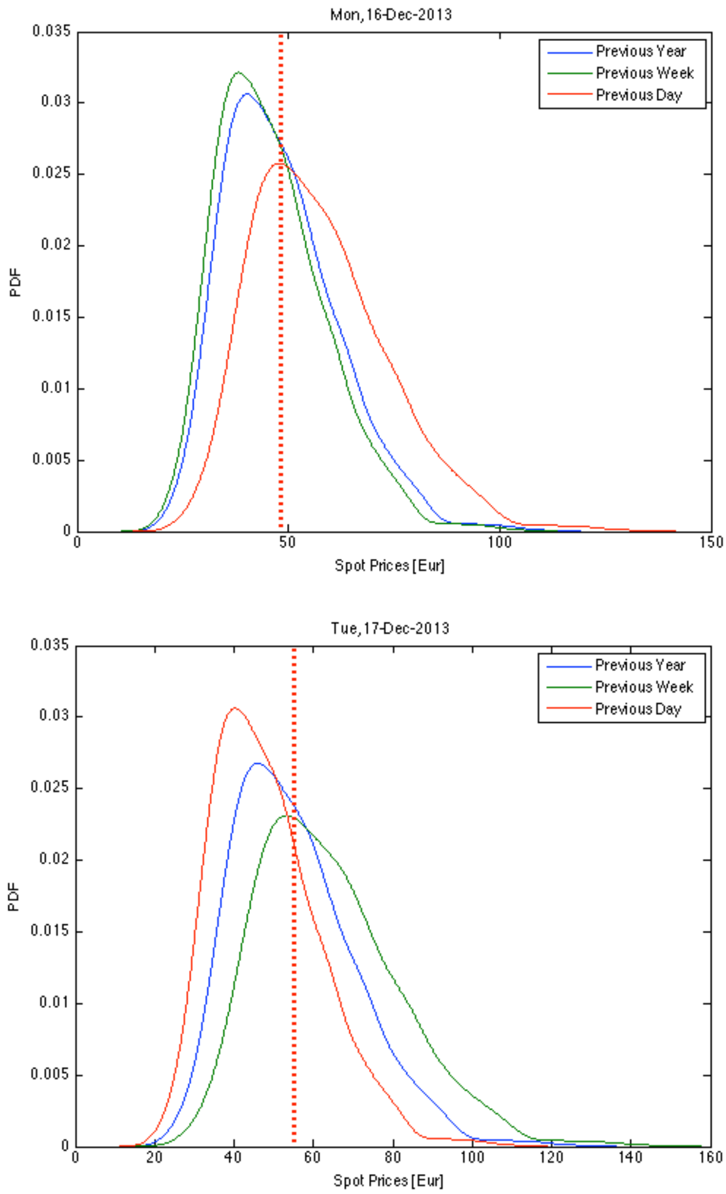

Figure 4.4 - Forecast of the day-ahead spot price using three different initial curves: from the previous year, previous week and previous day, for two different days: Monday (top) and Tuesday (bottom).

Three different initial curves are tested: from the same day of the previous year, same day of the previous week and from the previous day. The results are presented in Figure 4.4 for the first hour of each day.

In each of the previous graphic representations, three distribution density functions of the possible prices are drawn. These PDFs were computed with the above-mentioned method using the three different curves. With a vertical dashed line the real spot price of the first hour of each of the days is also represented.

Apart from Tuesday and from Friday (not represented), a good prediction of the price of the following day can be made using the curve of the previous day, as the realised price is very close to the median of the PDF.

4.3 - Intraday prices forecasting

In a first stage, the prediction of this variable was made using a similar method as seen in [4]. However, after consulting with OSIRIS, a new approach emerged.

Considering that markets are defined in such a way that arbitrage opportunities are immediately eliminated, then, it would be expected that the intraday prices would not be much different from the prices of the previous market. In fact, and as it was already shown in the previous Chapter, the difference between intraday and spot prices follow a Gaussian distribution not exactly centred (Figure 3.3).

As a result, intraday prices are predicted using the same method applied for the spot price, but using the current spot price as the initial curve.

When it is necessary to validate the different strategies in Chapter 6, the expected value of the distributions created is used, since the real intraday prices are unknown. This is expected value is in fact the spot price of the delivery day.

By doing so, any possibility for arbitrage between markets is completely eradicated, but the results obtained are more consistent. (The initial strategy led to situations of different intraday prices when testing different strategies that made impossible to take any definitive conclusions).

4.4 - Imbalance settlement prices forecasting

Given the importance of these prices to the conclusions of this work and because they are not so commonly forecasted (when compared to spot prices or wind power production), a deeper analysis on their forecasting was made. A similar approach of what was used in [12] and in [3] is preferred, rather than the options undertook in [9] and in [11]. Therefore, the forecast of the regulating market of [5] is enhanced and adapted to the present study.

A closer look to Table 3.1 will stand out the fact that at any given moment, the imbalance settlement price for positive and for negative imbalances are different. However, depending on the direction of the regulation, only one of them will be different from the spot price: if regulation is needed in the upward direction, then the negative imbalance price is different from the spot, if it is needed in the downward direction, then it is the positive imbalance price that is different.

The imbalance settlement price will, therefore, always be bounded by the spot price. Since there is already a tool to forecast the spot price, it is decided to subtract this price from the imbalance settlement prices and obtain two different prices a positive and a negative one. The positive price will represent the cost with upwards regulation and will be called Up Regulation Price, in reality this price is either zero or $PMP_h(1+k)$. The negative price will represent the costs with downward regulation and will be denominated Down Regulation Price, this price will be either zero or $\frac{PMP_b}{(1+k)}$. The decomposed imbalance settlement prices are shown bellow:

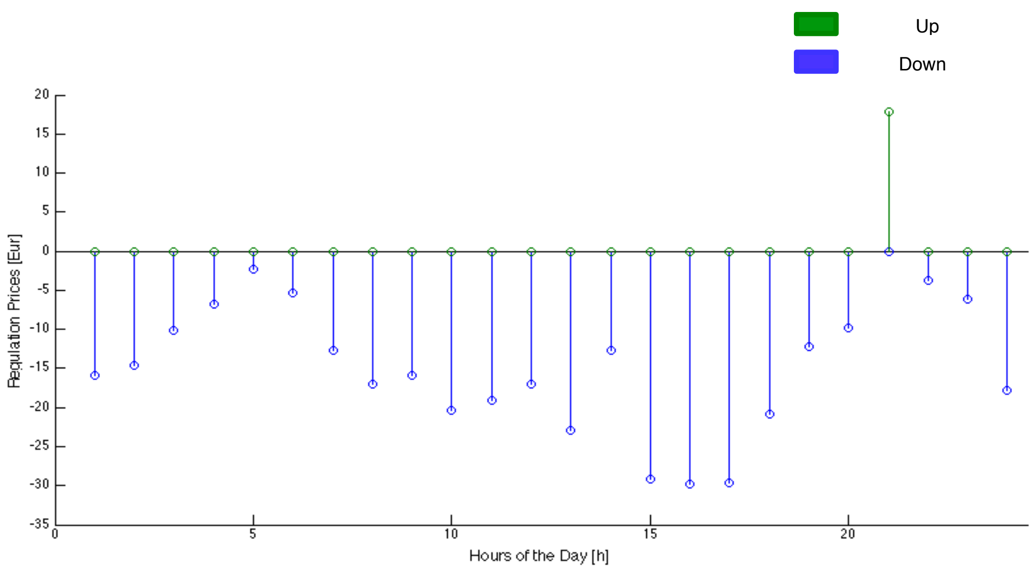

Figure 4.5 - Regulation Prices Predictions for 01/12/13

As can be seen in the example above, it is rather difficult to treat regulation prices as time series, since regulation in one specific direction happens for some hours and the time between different observations varies. A similar approach of what is done in the literature is carried out and price models are computed independently only with observations of each direction.

It is therefore decisive to predict in which direction the system would need regulation before estimating price models.

4.4.1 - Regulation direction forecasting

The first approach was to make use of the tool that was partially used for the wind power forecasting [13] to predict the direction of regulation.

This turned out to be the less efficient way of forecasting the system direction so a different approach is undertaken using classifiers. The accuracy of each method is calculated with

$$Accuracy = \sqrt{\frac{TP}{TP+FP}\frac{TP}{TP+FN}} \cdot 100 \tag{4.1}$$

as it is done in [6]. TP, FP and FN are, respectively True Positives, False Positives and False Negatives, which represent the number of times the method predicted the real direction (TP), the number of times it predicted a direction but failed (FP) and the number of times it did not forecast a certain direction and that direction is in fact the real one (FN). An overall of all the directions is calculated for each method. The following Table gives a clearer perspective of the values mentioned before:

Table 4.1 – Confusion Table

		Actual Value	
		yes	no
Hypothesis	Yes	TP	FP
	No	FN	TN

<u>The OPIUM[8] tool approach</u>

As a whole, the tool forecasts the needs of upward and downward reserves given a risk level and taking into consideration all sources of uncertainty in the production of electric power (among which is uncertainty in wind power). All of the uncertainty distributions where convolved into a PDF of the overall electric system uncertainty that is later used to determine the reserves.

An assessment of the volume of the reserves is then carried out in order to determine what would be the more likely direction of regulation.

However the tool predicted the necessities as a whole (PRC, SRC and TRC) from which only the TRC is of interest since is the one traded in the balancing market, as explained in Chapter 3.

According to [18] PCR corresponds to 600 MW in France. These are subtracted from the calculated reserves.

SCR depends on the gradient of variation of demand every 30 minutes. The rule is as follows:

[8] *Outil Probabiliste de calcul de l'IncertitUde et des Marges* (OPIUM) is the name of the tool developed in [13]

$$\mathrm{SCR} = \sqrt{10L + 150^2} - 150, \qquad \text{if} \quad \Delta L_{30min} < 6\ GW \tag{4.2}$$

$$\mathrm{SCR} = \frac{\Delta L_{30min}}{6}, \qquad \text{if} \quad \Delta L_{30min} > 6\ GW \tag{4.3}$$

where L is the load at that moment. The maximum value for SCR is 1450 MW.

Demand is therefore assessed and the corresponding value of SCR subtracted to the reserves forecasted by the original tool.

The volumes of reserves for upward and downward regulation are compared in order to deduce what would be the most probable direction of regulation. This turns out to be a rather imprecise method (only 33%[9] of accuracy in the predictions) as there are various cases of reserves being "dispatched" with the same volumes in opposite directions.

The forecast the direction in which the system is going to need regulation is done using classifiers. The goal is to decide, based on observations of explanatory variables, what would be the most probable direction of regulation.

Such explanatory variables are taken from a similar problem studied in the literature [19] and the classifiers are then tested for the whole year of 2013 using these variables:

- Day of the week (from 1 being Monday to 7 being a weekend day);
- Hour of the day from 1 to 24;
- Wind power penetration, defined as the ration between wind power production and demand;
- The balance of imports and exports;
- The spot price;
- Lagged observations of the regulation direction (24, 47, 48, 96, 120 and 168 hours before delivery).

<u>Logistic Regression</u>

The first classifier to be tested uses logistic regression, which assigns a direction of regulation to a set of observations of the explanatory variables using a logistic function. This is a type of statistical probabilistic classifier.

This is a binary classifier – it only assigns to one of two categories – so a model is trained to select if regulation is needed or not and another trained to classify in which direction that regulation would be needed.

An accuracy of only 58% is obtained. To improve this poor performance a stepwise regression is also implemented. The aim is to test different sets of the explanatory variables and find with which the best results are obtained. The performance worsens to 56%.

[9] When one classifies into two distinct categories a common benchmark is the throw of a coin, which has an accuracy of 50%. In this case, however, such benchmark does not hold, as classifications are made into three categories. We can, however consider the same principle: randomly assign an element to a category, which has an accuracy of 33% (1 out of 3 times is a success). The presented strategy is therefore equal to randomly defining the regulation direction.

<u>Naïve Bayes Classifier</u>

A different classifier is then tested using the same data and explanatory variables. This time computational intelligence is used. This classifier makes use of the Baye's Theorem with strong independence assumptions between features (the explanatory variables) so it is denominated as Naïve.

The results are not satisfactory: only 56% of accuracy is obtained.

As the training of the classifier and the predictions are made with a group for training and another for testing/predicting, a different method is implied: the use of a sliding window.

The concept is rather simple: instead of dividing the whole set of data into two groups, a single group of *Wd* observations and the corresponding explanatory variables, chronologically organised, is used to train the classifier. The following "array" of explanatory variables is then used to make the prediction. The oldest variables and observation are discarded. The new ones, the ones used for making the previous prediction, together with the real value of the direction are added to the training group. In a way the train group "slides" through the whole set of explanatory variables and observations and predictions become more accurate. It is now obtained an accuracy of 68%. The following diagram illustrates this principle:

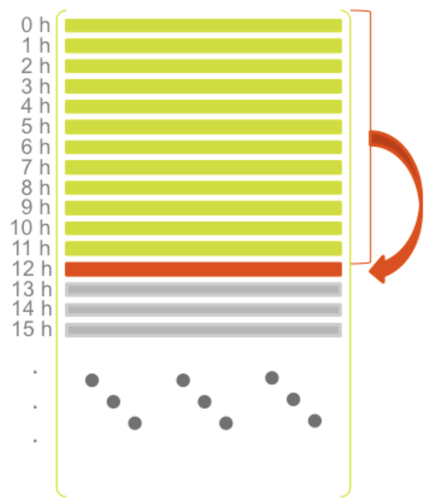

Figure 4.6 – Representation of the Sliding Window technic: a set of 11 observations was used to predict the 12th

Once the classifier is defined, some modifications have to be made to adapt it to the particularities of the problem in hands.

The main changes are related to the explanatory variables, since not all of them are available at the times decisions had to be made. Among them is the balance of importations and exportations of power. Only assigned capacities were available and forecasting these would add more noise to the prediction of the direction of regulation. These are not considered for simulation purposes.

The variables of the lagged observations are listed in the following Table accordingly to the market in which they are used (day-ahead or intraday) and accordingly to the different groups (training and predicting):

Table 4.2 – Lagged periods of observations of the regulation direction

	Day-ahead Market	Intraday Market
Train Group	96 and 216 hours before delivery	36, 60 and 170 hours before delivery
Predict Group	48 and 168 hours before delivery	24, 48 and 168 hours before delivery

Other variables are the spot price, which is replaced by the forecasted spot price to make predictions in the day-ahead market; the wind power penetration also have to be the forecasted one for the predictions in both markets; and then the hour of the day and the day of the week, which do not suffer any alteration.

Several different sized sliding windows are tested, with lengths from 1 hour to 24 hours and it is concluded that the one that leads to the best results is of a 16-hour length.

Initial results for a sliding window of 12 hours and then the 16-hour one are presented bellow. Together with the results for the day-ahead predictions:

Table 4.3 – Accuracy results for the predictions of regulation direction

	Accuracy		
Day	Day-ahead Market	Intraday Market (sliding window of 12 hours)	Intraday Market (sliding window of 16 hours)
Monday	54%	54%	80%
Tuesday	58%	63%	92%
Wednesday	92%	100%	100%
Thursday	67%	58%	92%
Friday	83%	75%	92%

The Naïve Bayes Classifiers outperforms the other methods analyzed: the OPIUM method is design to forecast volumes of reserves and these do not fully represent the real direction of regulation; and the Logistic Regression needs to make two sequential forecasts, as it first predicts whether or not regulation is necessary and then, in which direction.

4.4.2 - Regulation prices forecasting

Once the regulation direction is known, prices for up regulation and prices for down regulation are independently forecasted.

Such forecast is made using quantile regression: a regression method that provides the quantiles of the predicted values and, therefore a cumulative density function, which is the final goal of all the abovementioned forecasts. As mentioned in Chapter 2, the forecasting of the regulation direction price is based on the work of [5], as it was also done in [3] and in [12].

For making such regression the explanatory variables used are the spot price and the wind power penetration. A training group is created with observations from the previous two days (counting backwards from the delivery day) and from the same day of the previous week - corresponding to 24, 48 and 168 hours before delivery.

For the predicting group, the forecasted values of the explanatory variables are used for both markets, except for the spot price on the intraday market, which is already known at that time.

It is important to mention that up regulation prices are only forecasted using observations realised when the system is in need of up regulation and down regulation prices when the observations are of instants when the system is in need of down regulation.

For the predicting groups, firstly the forecast of the regulation direction is made and depending on the results a model for up regulation prices is implemented if the forecasted direction is upwards, or a model for down regulation prices if the direction is the opposite one.

The final imbalance settlement prices are reconstituted by adding the spot price - or the forecasted spot price, depending on the market:

$$Up\ regulation \begin{cases} \pi_{IS}^{+} = \pi_{DA} \\ \pi_{IS}^{-} = \pi_{DA} + \pi_{BM}^{Up} \end{cases} \quad (4.4) \qquad Down\ regulation \begin{cases} \pi_{IS}^{+} = \pi_{DA} + \pi_{BM}^{Down} \\ \pi_{IS}^{-} = \pi_{DA} \end{cases} \quad (4.5)$$

where π_{IS}^{+} and π_{IS}^{-} are, respectively, the positive and the negative imbalance settlement prices; π_{DA} is the day-ahead spot price and π_{BM}^{Up} and π_{BM}^{Down} are the up and down regulation prices, mentioned in the beginning of this section.

Figure 4.7 illustrates randomly selected prices from the CDF corresponding to the first day of December of 2013:

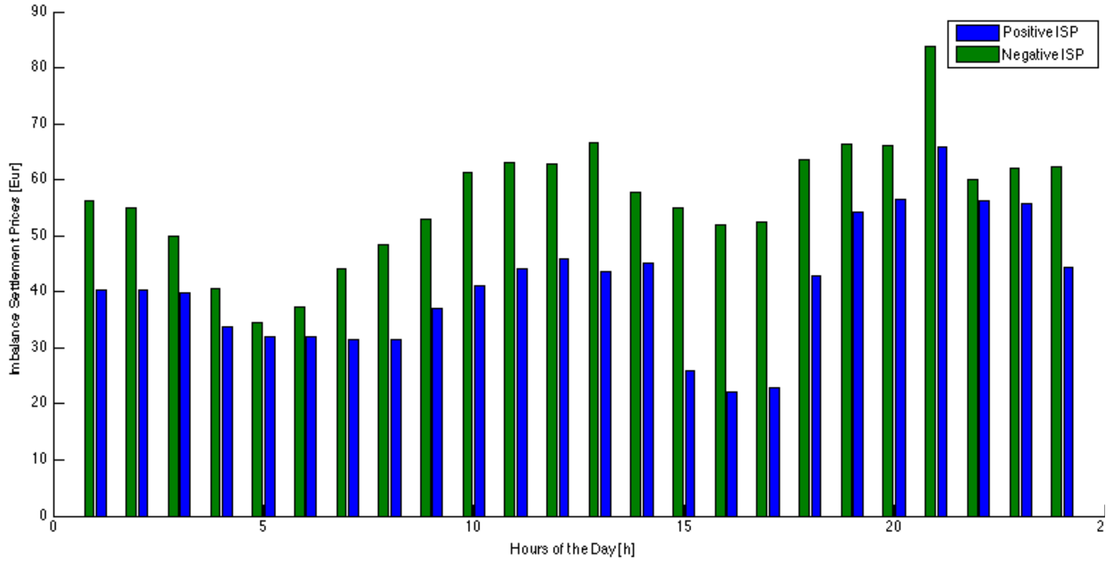

Figure 4.7 – Imbalance settlement prices forecasted for 01/12/13

The above-mentioned methods were carried out in order to compute distinct possible values of wind power production and market prices, which were used to create the random scenarios for the Monte Carlo simulation. This process is further detailed in the following Chapter.

Chapter 5

Methodology

Some of the bidding strategies studied depend on the definition of an optimal bid that both maximises the revenues of the VGP and minimises its impact on the system – its imbalances.

To find such a bid, a Monte Carlo Method is used.

This method is the systematic application of the probabilistic principle of sampling. Its goal is to predict the value of a given test function using a series of different scenarios (containing different values for the independent variables of the test function). The expected result of that function when it is calculated under the different scenarios will tend to the expected value of the test function.

Different bids are therefore submitted to a Monte Carlo Simulation that recreates what could be the expected outcome for the VGP if he had selected that bid. The one that leads to the maximum revenue and exposes the VGP to the minimum loss is defined as optimal and is the selected one.

This section carries on to give a brief explanation of what is a Monte Carlo Method and proceeds to explain the decisions taken and the different bidding strategies tested. Further details on this method can be found in [20].

5.1 - Problem formulation

The VGP will participate in the day-ahead and intraday markets, in which he will always be a price taker. He will, therefore, make offers in terms of quantities and not prices. After delivery, he will either receive or pay a compensation for its imbalances. The function below represents its overall revenues and all variables correspond to a specific hour:

$$R(W_{DA}, W_{ID},) = \sum_{h=1}^{24} \left(\pi_{DA_h} W_{DA_h} + \pi_{ID_h} W_{ID_h} + \pi^{+}_{IS_h} \Delta^{+}_{IS_h} - \pi^{-}_{IS_h} \Delta^{-}_{IS_h} \right), \tag{5.1}$$

where W is the power bid in day-ahead (index DA) or intraday (index ID) markets. Δ^{+}_{IS} and Δ^{-}_{IS} are the positive and the negative imbalances and are defined as the difference between the power delivered and the power traded:

$$\begin{cases} \Delta^{+}_{IS} = W_R - (W_{DA} + W_{ID}), & if \quad W_R > (W_{DA} + W_{ID}) \,, & (5.2) \\ \Delta^{-}_{IS} = (W_{DA} + W_{ID}) - W_R, & if \quad W_R < (W_{DA} + W_{ID}), & (5.3) \end{cases}$$

where W_R is the wind power delivered.

The decisions of the VGP regarding its bidding for a given horizon are independent of both past and future horizons. This would not be the case if power storage was also being considered.

As a price-taker, price is constant and independent from the bid placed. Hence, revenue is only limited by the imbalance costs.

Minimising these, as proposed by the title of this document, is maximising those. Consequently, the bid that maximises revenues is the same that minimises imbalance costs.

The maximization of the function $R(W_{DA}, W_{ID})$ will therefore be this problem's test function in the Monte Carlo simulation.

For every bid for the day-ahead or for the intraday markets that is tested, a series of scenarios of the possible states of market prices and of wind power production are created. Under these scenarios the different bids are tested and their performance will help the VGP to make a decision regarding which one to use in his strategy.

5.2 - General concepts of the Monte Carlo Method

In order to determine the expected outcome of a given situation – expressed by means of a test function, using the Monte Carlo Method, one submits his test function to different scenarios. In this case, the test function will be the above-mentioned function $R\ (W_{DA}, W_{ID})$.

Each one of these scenarios consists in a set of possible states in which each stochastic variable may reside: market prices, wind power delivered and bids placed in the day-ahead and in the intraday markets. Associated to each possible state X of the variable i, there is a probability $p\ (X_i)$ of the likelihood of i being in the state X. If one was to consider all the possible scenarios, with all the possible combinations of states, one would be able to determine the real expected value $E(R)$ of the test function $R\ (W_{DA}, W_{ID})$.

However, given a finite number of scenarios the best that can be achieved is an estimation of $E\ (R)$, hereafter referred to as $\hat{E}\ (R)$. As it occurs in any other sampling method, the uncertainty of this estimation of the expected value can be represented by a variance $V\,(\hat{E}(R))$

$$V(\hat{E}(R)) = \frac{V(E)}{N}, \tag{5.4}$$

or by an unbiased sample variance $\hat{V}(R)$, since the real variance is also unknown:

$$\hat{V}(R) = \frac{1}{N-1}\sum_{s=1}^{N}\left[F(X^s) - \hat{E}(R)\right]^2, \tag{5.5}$$

where N is the number of scenarios used. Since $\hat{V}(R)$ is inversely proportional to the dimension of the sample (N), it is usual to use it as a convergence criterion of the Monte Carlo Simulation, expressed in a coefficient of variation squared:

$$\beta^2 = \frac{\hat{V}(R)}{(\hat{E}(R))^2}, \tag{5.6}$$

or in terms of the standard deviation σ,

$$\beta = \frac{\sigma(\hat{E}(R))}{\hat{E}(R)}, \tag{5.7}$$

The simulation should be run until this coefficient is lower than a pre-established threshold: the convergence criterion.

5.3 - Convergence Criterion

Once the unbiased sample variance is known, a confidence interval can be determined. In other words, one could calculate an interval of possible values of $\hat{E}(R)$ that would contain the real expected value with a desirable probability.

In the present work, such a confidence level is calculated for a probability of 99%.

The probabilistic density function of a normal distribution (with zero mean and a standard deviation of 1), represented in Figure 5.1, illustrates the process undertook.

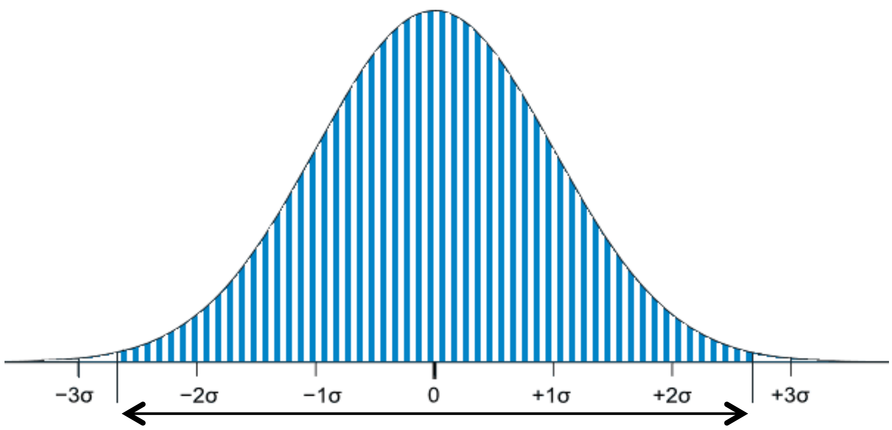

Figure 5.1 - PDF of a normal distribution and an interval of $[\mathbf{-2,575\sigma, +2,575\sigma}]$ that corresponds to a probability of 0,99

By calculating the integral of the PDF that corresponded to 0,99, the interval $[-2{,}575\sigma, +2{,}575\sigma]$ is obtained. This confidence interval can also be represented as

$$\mathrm{CI}(99\%) = \left[\hat{E}(R) - 2{,}575\sigma\left(\hat{E}(R)\right), \hat{E}(R) + 2{,}575\sigma\left(\hat{E}(R)\right)\right], \quad (5.8)$$

$$=> \hat{E}(R) \pm 2{,}575\sigma\left(\hat{E}(R)\right), \quad (5.9)$$

$$=> \hat{E}(R) \pm 2{,}575\frac{\hat{\sigma}}{\sqrt{N}}, \quad (5.10)$$

However,
$$=> \hat{E}(R) \pm 2{,}575\hat{E}(F)\beta, \quad (5.11)$$

So, an interval of $\hat{E}(R) \pm 1\%$ and with a confidence level of 99% can be obtained if $2{,}575\beta = 0{,}01$, which means for a $\beta = 0{,}004$.

5.4 - Risk criterion

As defined by Clemen, cited in [9], risk is the state of having imperfect knowledge of a future outcome that can involve an undesirable situation, being a loss or a catastrophe. It can be measured by associating a set of possible future outcomes, with quantified losses and probabilities of them becoming true.

In the current problem, risk is assessed by the Value at Risk (VaR), which is a financial measure created to quantify the exposer to risk of a portfolio of a company [17].

It is defined as the maximal expected loss with a given probability α and expressed in monetary units, in this case a $\mathrm{VaR}_{5\%}$ was calculated in euros [€].

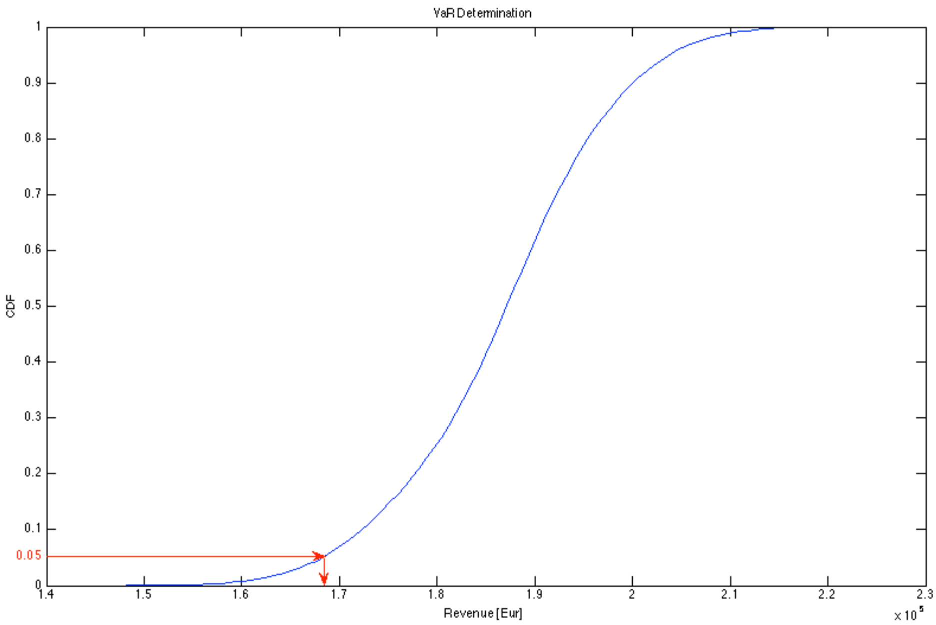

Figure 5.2 – $\mathrm{VaR}_{5\%}$ calculation: the revenue that corresponds to the 5% percentile is selected from the CDF of possible revenues.

The $VaR_{5\%}$ is calculated by determining the revenue that corresponds to the percentile of 5% of the distribution of revenues: by computing the inverse CDF of possible revenues and obtaining the revenue for 0.05.

Usually, the value obtained is negative, i.e. it corresponds to a loss. Thus, the $VaR_{5\%}$ will be the absolute value of that quantity.

However, in the case of that amount being positive, as it is shown in Figure 5.2, the $VaR_{5\%}$ will not represent a real "value at risk", but rather the maximum revenue obtained in 5% of the cases. Another way to put it would be that 95% of the revenues are greater than $VaR_{5\%}$.

As a result of this being the situation of all the assessed bids, the $VaR_{5\%}$ will be from now on referred to as the Minimum Assured Revenue 5% ($MAR_{5\%}$).

5.5 - Sampling method

To create the various scenarios, samples are taken from the probabilistic forecasts created beforehand. This is done by computing the CDFs of the probabilistic forecasts and randomly selecting one of the percentiles. Figure 5.3 illustrates the process.

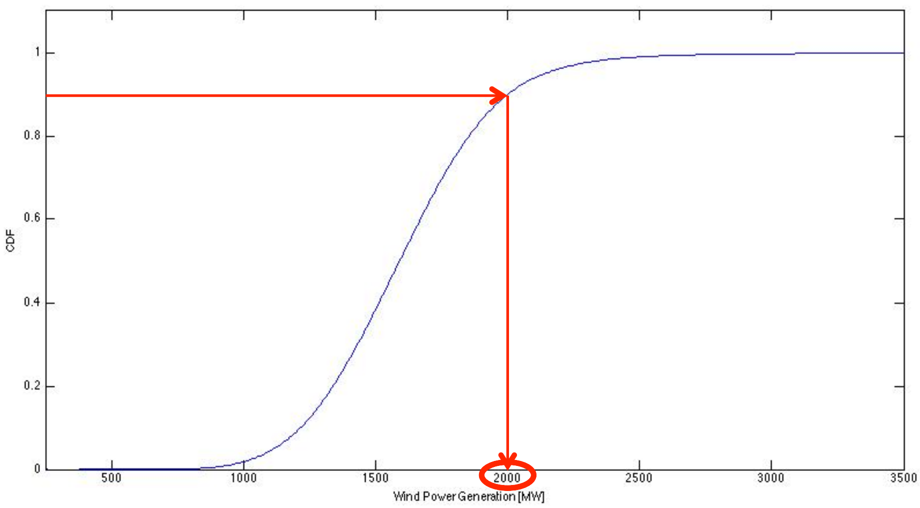

Figure 5.3 – Random election of a value of wind power production to be included in one scenario

The process is carried out to all the variables forecasted: wind power, day-ahead prices, intraday prices and imbalance settlement prices.

The percentiles that are randomly generated are always different. Hence all the selected variables that create a scenario are independent from one another.

The different bids and the different strategies are analysed with the same scenarios, in order to be possible to take conclusions from the results of the various simulations.

5.6 - Algorithm

The algorithm is repeated for all the hours of the day and for all the pre-defined bids. These are created to be close to the expected value of the point forecast for the same reasons presented in [12]: if bids were very far from the point forecasts, it would seem that the VGP was taking advantage of the market and could be penalised for that. Moreover, high imbalances could influence the imbalance settlement price formation and invalidate the price-taker assumption.

In addition to those, since it is assumed that there is little to no possibility of arbitrage between the day-ahead and the balancing mechanism, the VGP is forced to keep his imbalances as small as possible in order to avoid possible losses. Note that the total revenue includes not just the VGP's profits from market participation but also the payment for deviations. Therefore, he would always be leaned to bid close to its point forecast.

Bids are tested under several scenarios. For each one of them, the revenue is calculated using the value of wind power bid, market prices and the delivered wind power. After simulating all the necessary scenarios for the method to converge, the expected revenue and the $VaR_{5\%}$ - the $MAR_{5\%}$ - are calculated.

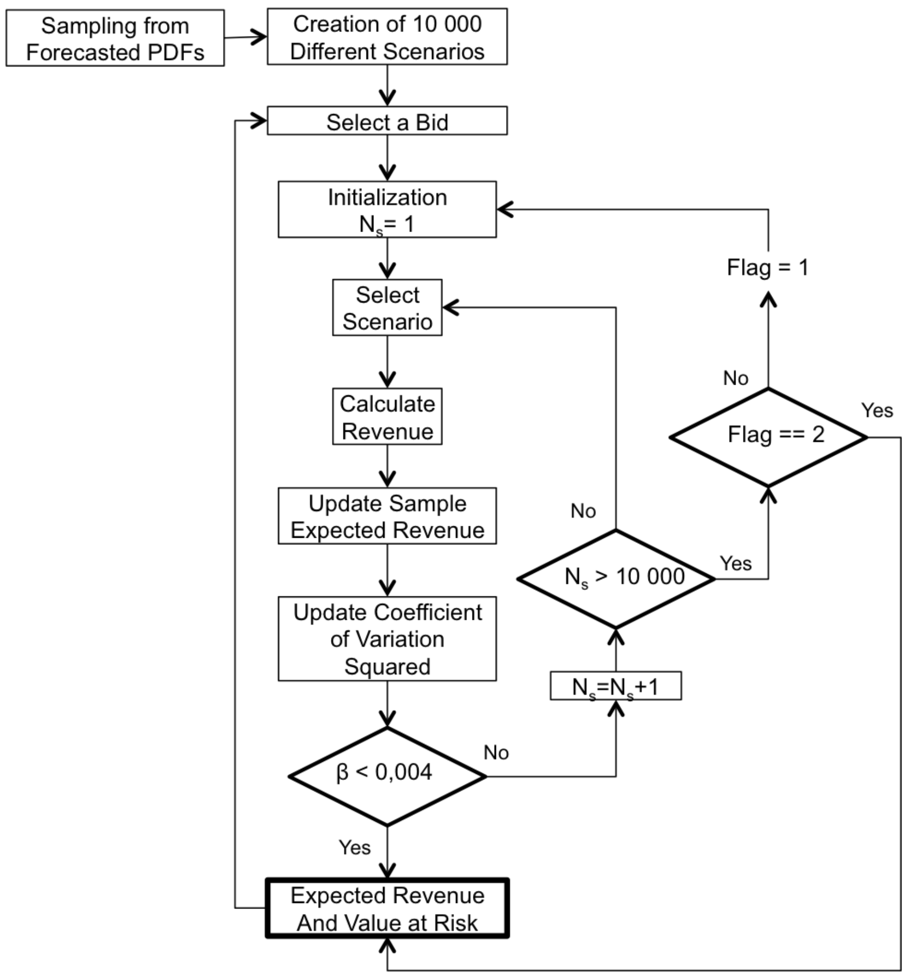

Figure 5.4 – Algorithm of the Monte Carlo Simulation

This means that for each bid corresponds an expected value of the revenue and a $MAR_{5\%}$. Using these two criteria the VGP will decide which bid to choose for each market it is participating in and for every hour of the day of delivery.

The flow chart from Figure 5.4, details the algorithm implemented.

The process starts with the creation of the different scenarios. An initial batch of 10 000 randomly generated scenarios is created from samples taken from the probabilistic forecasts of wind power production and market prices, accordingly to the sampling method of Section 5.5.

Once a bid is placed, it is simulated for one scenario and the revenue is calculated. If convergence is not achieved, another scenario will be simulated. The process is repeated until either the convergence criterion is smaller than the threshold or two batches of scenarios are used. In the latter case a flag would be signalled and conclusions could not be taken for that bid at that hour. In the analysed case study this was never the case.

At the end of the process the expected revenue of the bid that is being tested is saved and the Value at Risk is computed.

Once all the pre-defined bids are tested, an Expected Revenue / VaR plot can be obtained in order to present the non-dominated[10] bids.

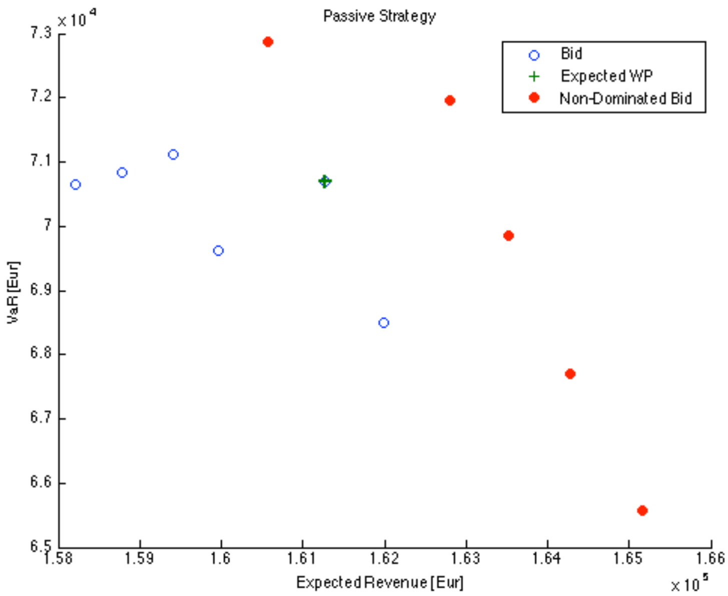

Figure 5.5 - Results of the simulation of the different bids and the bid corresponding to the point forecast, for the 18th hour of 16/12/2013 using the Passive Strategy

[10] Non-dominated solutions are those that cannot improve in value one of the objective functions, without degrading some of the other objective values.

As a result of the meaning of VaR in the context of the present work, the VGP will choose a bid that maximises both the expected revenue and the VaR. From the Figure above, the bids closer to the upper right corner are the ones that provide a possible solution.

Although more than half of the bids considered can be disregarded, the VGP still has to opt from five different bids, being now faced with a decision problem.

To fully elaborate on the decision problem is not an objective of this dissertation. However, the basis for a future analysis is going to be set.

The VGP will have to maximise the following objective function:

$$V(W) = \hat{R}(W) + k \cdot VaR_{5\%}(W) \tag{5.12}$$

where W is the wind power bid by the VGP, $V(W)$ is the objective function to maximise, $\hat{R}(W)$ is the expected revenue, k is a trade-off between the expected revenue and the Minimum Assured Revenue (MAR) and $VaR_{5\%}(W)$ is the MAR.

For a high k, the VGP is more interested in maximising its MAR, rather than its expected revenue. It is, therefore, risk averse. If on the other hand, the k is low or null, the VGP is risk prone and is more interested in maximising its expected revenue.

The decision will result from the knowledge the VGP gains from real situations and also from its own preferences.

It is important to emphasise that the direct application of (5.12) will not lead to all the non-dominated solutions, as pictured in Figure 5.5. This is due to the fact that some of the non-dominated bids are inside the convex part of the Pareto front and therefore cannot be reached by $V(W)$, despite the value of k.

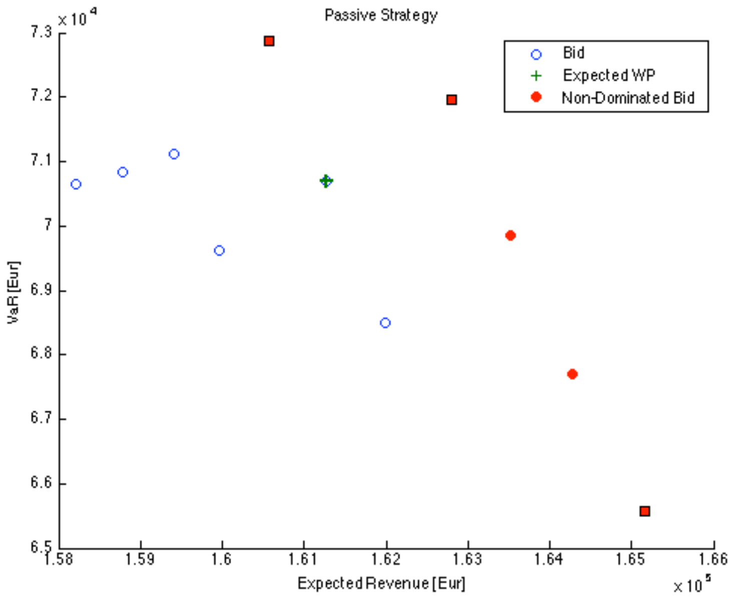

Figure 5.6 - Results of the simulation of the different bids, the bid corresponding to the point forecast and the bids resulting from the maximization of $\boldsymbol{V(W)}$, for the 18th hour of 16/12/2013 using the Passive Strategy

The square-shaped bids correspond to the non-dominated bids “detected” by (5.12). The other non-dominated bids, despite not being selected by (5.12) are equally viable options for the VGP.

With the information regarding the positioning of the different bids in the Expected Revenue / Minimum Assured Revenue axis, the VGP will have additional information to choose his final bid. As mentioned before, the study of the decision problem is not an objective of this work, therefore no further analysis was undertook.

However, in order to drawn conclusions regarding the different strategies, it is necessary to consider a criterion to choose from the different non-dominated bids. This means that it is compulsory to define the profile of the VGP regarding his aversion to risk.

For the case study scrutinised in the following Chapter, the VGP will be considered to give more emphasis to the maximization of his expected revenue. Hence, he will be regarded as risk-prone.

5.7 - The Different strategies

Four different strategies are tested in Chapter 6 and presented on the Table below. Table 5.1 also includes the benchmark case that corresponds to what is commonly done today by a VGP: bids for the day-ahead market are made based on the point forecasts of the VGP’s wind power; no action is taken in the intraday market as it is considered that this market has low liquidity, and during the imbalance settlement it will pay its imbalance costs.

Table 5.1 – Variables involved in the different strategies

	Benchmark	Improved Benchmark	Passive	Active	Active Fully Optimised
DA Price	π_{DA}	π_{DA}	$\hat{\pi}_{DA}$	π_{DA}	
DA Bid	$\widehat{W}_{DA}$	$\widehat{W}_{DA}$	$[\widehat{W}_{DA}]_b$	$\widehat{W}_{DA}$	$[\widehat{W}_{DA}]_b$ [11]
ID Price	-	π_{DA}	-	$\hat{\pi}_{ID}$	
ID Bid	-	$\widehat{W}_{ID}$	-	$[\widehat{W}_{ID}]_b$	
Positive Imbalance	$W_R - \widehat{W}_{DA}$	$W_R - (\widehat{W}_{DA} + \widehat{W}_{ID})$	$W_R - [\widehat{W}_{DA}]_b$	$W_R - (\widehat{W}_{DA} + [\widehat{W}_{ID}]_b)$	
Negative Imbalance	$\widehat{W}_{DA} - W_R$	$(\widehat{W}_{DA} + \widehat{W}_{ID}) - W_R$	$[\widehat{W}_{DA}]_b - W_R$	$(\widehat{W}_{DA} + [\widehat{W}_{ID}]_b) - W_R$	
IS Price	$\pi_{IS}^{+}, \pi_{IS}^{-}$	$\pi_{IS}^{+}, \pi_{IS}^{-}$	$\hat{\pi}_{IS}^{+}, \hat{\pi}_{IS}^{-}$		

[11] This bid is the one resulting from the Passive Strategy.

The above-mentioned approaches are made by VGPs that are only focused on the physical aspect of energy trading. In order to account as well for market price formation, three different strategies were also proposed.

The first strategy is an enhancement of the benchmark case: after bidding in the day-ahead market, the VGP will try to correct its position by also bidding in the intraday market. This situation corresponds to a near future when intraday markets will have more liquidity. By using the updated wind power forecasts made with local meteorological measures and data collected in its wind farms (turbine outages, maintenance stops, among others), the VGP will correct its position in intraday markets. Although it is considered as a strategy, the Improved Benchmark involves no decision regarding bids, as the expected wind power production is bid in day-ahead and corrected in the intraday market.

The Passive Strategy is similar to the benchmark case, but instead of the expected value of wind production, an optimised bid is placed. Such optimization is done using the aforementioned algorithm. This strategy would be used if the considered intraday market had little to no liquidity.

The Active Strategy is based on the premise that optimization in day-ahead is difficult due to the great time gap between the time the decision is made and the delivery hour. It consists in bidding the expected wind power production in day-ahead and optimising the bid of the intraday.

The last strategy takes the result from the passive strategy – an optimised day-ahead bid – and then proceeds to optimise the intraday bid.

Chapter 6

The Case Study

The different strategies are tested for a VGP that is responsible for the entire wind power production in continental France. The installed capacity of the global wind farm in 2013 totalled 7670 MW, however the load factor was never higher than 55% during the period studied.

This period corresponds to the working days of the 51st week of 2013. January and December are usually the months with more wind power production, however the week from the 16th to the 20th of December was the one with more power production:

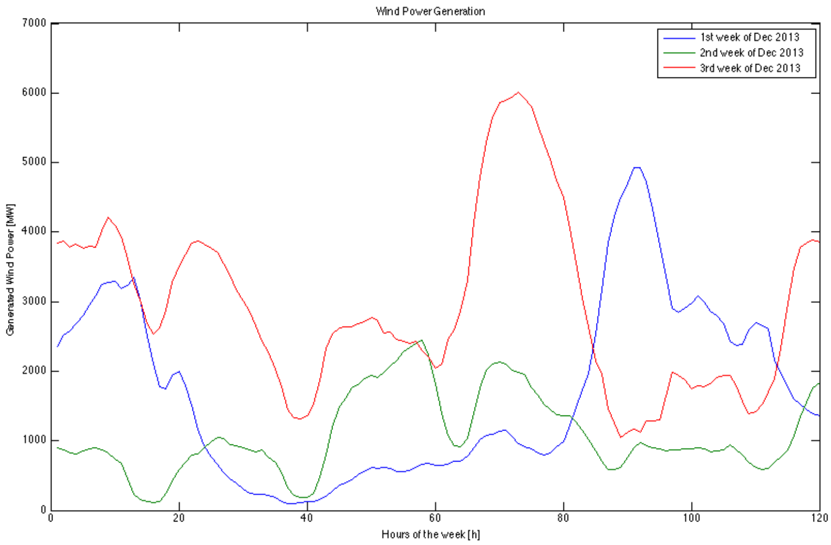

Figure 6.1 – Wind power production in the first three weeks of December 2013

The month of January had lower production than December, so it does not appear on the previous Figure. In addition to this, the last week of December was not considered, as it corresponds to a period of holidays. This means that consumption is reduced and a conclusive analysis of the different strategies could not be achieved.

Only working days were tested in order to avoid different seasonal effects between working days and weekend days. A similar approach can be seen in [8].

6.1 - Available Data

All the data used in the simulation is public and can be found in [22], for data regarding the day-ahead market and in [23] for all the information related to production, demand and imbalance settlements.

The realised day-ahead spot prices, wind power forecasted load factors and demand forecasts are needed for day-ahead decisions. The intraday trading was done using the spot prices of the same day, as the actual traded price is unknown. This approach is reasonable if the no-arbitrage assumption is considered.

For the imbalance settlement it is necessary to obtain the positive and the negative imbalance prices, the direction of regulation of the system and the delivered wind power.

6.2 - Results

The different strategies are applied to each day considered in the case study. As decisions are time-independent, each hour is assessed individually for all the pre-defined bids. The result from one hour of one of the days is similar to the example shown in the previous chapter (Figures 5.5 and 5.6), considered, in that case, for the first hour of the 18th hour of the 16th December 2013, using the Passive strategy.

The result shows that the more power is bid during the short-term markets (in this case only day-ahead), the more is earned globally.

This can be explained by the fact that during this day forecasts were pessimists and the actual delivered power was higher than expected. Wind power bid and delivered for that day can be visualised in Figure 6.2.

As previously mentioned, the VGP’s risk attitude (despite being defined as risk averse) do not influence the choosing of the optimal bid, as imbalance costs are small when compared to the overall winnings (Table 6.1).

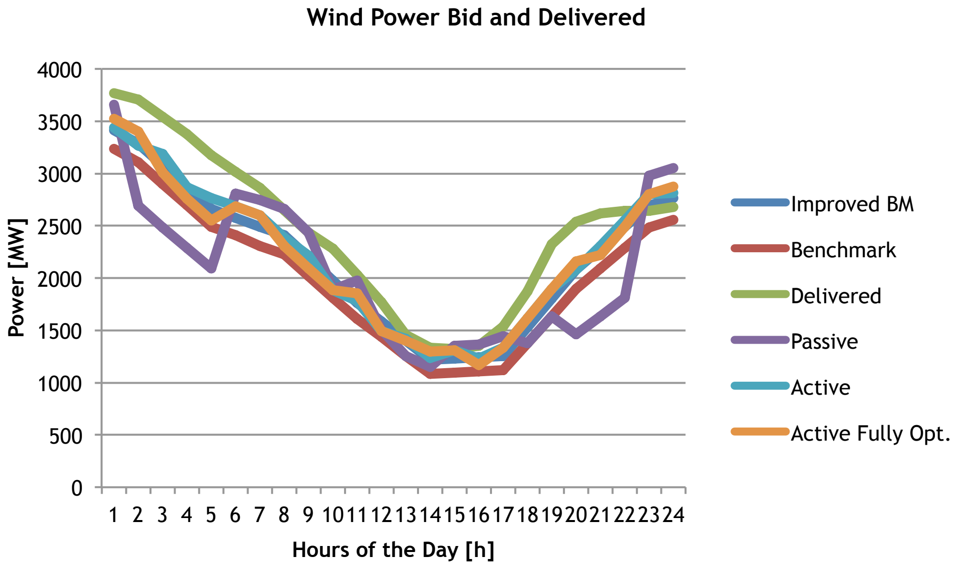

Figure 6.2 - Wind power bid in each strategy and delivered for the 17th of December 2013.

Table 6.1 - Comparison of total costs and revenues of the different bidding strategies

	Cost/Revenues
Improved BM	5,4%
Passive	6,9%
Active	5,3%
Active Fully Opt.	5,3%

6.2.1 - Comparison of the different strategies

The following Table shows how revenues were improved from the implementation of all the four different strategies.

Table 6.2 - Improvement in revenues comparing to the Benchmark case

	Benchmarks		Passive Strategy		Active Strategy		Active Fully Optimised	
Day	Benchmark	Improved Benchmark	Benchmark		Benchmark		Benchmark	
16	€4.602.965	-0,2%	-0,4%		0,2%		0,2%	
17	€3.469.722	1,9%	-0,8%		2,6%		2,3%	
18	€4.085.524	1,2%	1,3%		1,6%		1,6%	
19	€3.288.613	0,3%	0,2%		0,8%		0,8%	
20	€2.678.597	2,1%	3,8%		3,2%		3,2%	
Overall	€18.125.421	1,0%	0,6%	€115.419	1,5%	€276.172	1,5%	€269.353

A 1,5% improvement could be obtained by using either the Active or the Fully Optimised Active strategies. It is also evident the advantages in participating in intraday markets in order to further enhance revenues (Improved Benchmark, Active and Fully Optimised Active Strategies).

This is more evident when comparing similar strategies which the sole different is regarding intraday participation:

Table 6.3 - Improvement resulting from the participation in intraday markets

Active / Passive		Improved Benchmark / Benchmark	
1%	€160.753	1%	€174.525

It is interesting to compare the different strategies to the utopic scenario of having full knowledge of the wind power production. By doing so it is possible to evaluate how distant the revenues from each strategy are to the highest possible one.

The revenues that result from the various strategies will be represented by a fraction of the revenues from the unreal situation of having perfect knowledge:

Table 6.4 – Comparison of revenues from the different strategies to a perfect knowledge scenario

	Revenues					
Day	Perfect Knowledge	Benchmark	Improved BM	Passive	Active	Active Fully
16	€4.648.079,39	99,0%	98,9%	98,6%	99,2%	99,3%
17	€3.678.872,87	94,3%	96,1%	93,6%	96,7%	96,5%
18	€4.228.202,16	96,6%	97,8%	97,9%	98,2%	98,2%
19	€3.353.739,35	98,1%	98,4%	98,2%	98,9%	98,9%
20	€2.891.449,38	92,6%	94,6%	96,2%	95,6%	95,6%
Overall	€18.800.343,15	96,4%	97,3%	97,0%	97,9%	97,8%

Although very similar, it is the Active strategy that provides revenues closer to the maximum possible, which further stresses the importance of intraday market participation, resulting from the time-dependency of forecasts and the strict relation between reduction of imbalance costs and better forecasts.

Table 6.5 gives insight on the volumes of imbalances created in each strategy, when comparing to the benchmark.

It is evident that imbalances are reduced in all the strategies but the Passive one. This is an expected result, as revenues are solely limited by the imbalance costs. Reducing these will inevitably lead to higher revenues.

Once again is the Active strategy that produces the best results.

Table 6.5 - Volume of imbalances resulting from the different strategies

Day	Benchmark	Improved BM	Passive	Active	Active Fully
16	7.210 MW	5.324 MW	14.526 MW	5.761 MW	5.345 MW
17	10.687 MW	6.902 MW	10.711 MW	6.353 MW	6.914 MW
18	10.325 MW	7.489 MW	9.017 MW	7.427 MW	7.427 MW
19	7.674 MW	7.918 MW	8.852 MW	7.845 MW	7.882 MW
20	10.748 MW	7.805 MW	6.301 MW	7.086 MW	7.086 MW
Overall	46.643 MW	35.437 MW	49.407 MW	34.472 MW	34.654 MW
		-24,0%	5,9%	-26,1%	-25,7%

All in all, the reduction in volume of imbalances is not followed by a similar increase in revenues. This supports the motivation of the present work, when it was stated that VGPs are not incentivized to reduce their imbalances.

By selecting an active position, the VGP can improve its earnings in 31%, when compared to the costs he would have by using the benchmark approach. This represents 10% more than what he would obtain if he opted for participating in the intraday market, but not optimising its bidding.

No arbitrage was considered between the spot and the intraday markets: this is not true for every case, although 98% of the times the deviations between day-ahead and intraday market prices are less than 25€/MWh [16]. If arbitrage would be considered, the profits would be higher, as the optimization method would exploit these situations.

As it was also concluded in [4], [7] and [8], there is no real advantage in optimization in day-ahead, due to the difficulty in anticipating intraday and IS prices. Therefore the strategy of an Active VGP that does not optimise its biddings in the spot market outperforms the Fully Optimising Active strategy.

It is therefore preferable to offer the expected wind power production in day-ahead and optimise the offer in the intraday market, where a better anticipation of the prices can be achieved.

The following Chapter sums up the main results and draws conclusions of this work and it also makes suggestions for future developments on the problem under analysis.

Chapter 7

Conclusions and Future Developments

The motivation of this work was to provide insight on the balancing mechanism in France, by assessing the cost of imbalances of a VGP, and also to evaluate the impact of different bidding strategies in the imbalance costs. The main objective was to set a basis for further work with scenarios that included higher level of VG penetration.

To do so, three bidding strategies were tested with historical data of wind power and market prices and compared against a benchmark. These strategies included optimal bids that were created using a Monte Carlo Simulation, where the different variables used to calculate the test function were obtained from probabilistic forecasts. Such forecasts were made using existing tools at EDF and from the literature.

In brief, the overall results show that a better performance of the participation of the VGP in the short-term markets can be obtained by making use of all the available markets and by optimising its bidding. This is because bids are dependent on forecasts which depend on the time lag between the moment they are made and the moment of delivery: as close as one is to delivery time, the better the knowledge one has on its variable production.

In the literature, the curtailment of power is considered, when imbalance settlement prices are negative and lower than the selling price. This tends to improve the revenues, but was not considered in this methodology. The reason for that was that the curtailment of power would compromise the security of the system if we consider that all market players could be incited to change their positions at the last minute. This would not favour the system, as it would go from a position of excess of production to another of scarcity. Moreover, this is not authorised by the TSO.

Better results were obtained in the literature, for instance in [11] 18% of reduction of imbalance penalties was obtained. This is explained by the fact that in the studied market, the VGP was only penalised if imbalances were in the opposite direction of regulation.

Revenues of the VGP would also improve if a different market design would be implemented, as the current one does not incentivize the reduction of imbalances.

Nonetheless, the proliferation of optimised bids for different VGPs will make them non-optimal, as higher imbalances would make the VGP a price-maker. This was also concluded by [12].

The methodology created is sufficiently general in order to be enhanced with more resilient and accurate forecasting tools. It is also easily adaptable to other market designs and can even be used to simulate future scenarios of a higher degree of wind power penetration.

With this last approach returns are expected to increase, not only because traded volumes are higher, but also due to a better use of the optimization of the bids.

Glossary

Autoregressive Integrated Moving Average – model used to analyse or predict future values of a time series.

Balance Responsible Entity - Balance Responsible Entity is a market participant or a chosen representative responsible for its imbalances.

Balancing - All actions and processes undertaken by the TSO in order to ensure that the totality of electricity withdrawals are equalled by the totality of injections in a continuous way, as to maintain the system frequency within a predefined stability range.

Balancing Energy - Energy (MWh) activated by the TSO to maintain the balance between injections and withdrawals.

Balancing Mechanism - Balancing service secured by the TSO from the BSPs that consists in the activation of the offers made for the TCR in a pay-as-bid auction in which the TSO is the sole buyer.

Balancing Reserves / Capacities Reserves - Power capacities (MW) available for the TSO to balance the system in real time. These capacities can be contracted by the TSO with an associated payment for their availability and/or be made available without payment. Technically, reserves can either be automatically or manually activated.

Balancing Services - Balancing Reserves or Balancing Energy.

Balancing Services Provider - Market participant that provides balancing services to the TSO.

CPLEX - The CPLEX Optimiser is an optimization software package named for the simplex method as implemented in the C programming language, although today it also supports other types of mathematical optimization and offers interfaces other than just C.

Commission de Régulation de L'Énergie - Energy Regulation Commission is the French energy regulator responsible for the approval of the rules regarding the creation of the programs, the balancing mechanism and the adjustment charges, as well as the imbalance settlement prices.

Day Ahead Market - Also known as the Spot Market, it is the market in which parties can submit bids and offers to secure energy and sometimes also capacity for delivery on the following day. This market is operated by EPEXSpot.

Electricité de France - Electricity of France is a French electric utility that also acts as a BRE.

Energy Price - Volume price per MWh of electricity per trading period.

European Network of Transmission System Operators for Electricity - is the organization that regulates and represents all TSOs in the European Union and others connected to their network, for all regions, and for all their technical and market issues.

EPEXSpot - Is an international power exchange that covers France, Germany, Austria and Switzerland. It settles both the day-ahead and the intraday markets in France.

Ex-post trading - Trading scheme where parties can trade open positions after real time to adjust their imbalances in the final settlement.

Forecasted Load Factor – Ration between the wind power production point forecast and the installed capacity of wind power generation.

Frequency Containment Reserves - consist in the PCR mentioned bellow but under the new ENTSO-E terminology.

Frequency Restoration Reserves - consist in the SCR mentioned bellow but under the new ENTSO-E terminology.

Generalised Autoregressive Conditional Heteroskedasticity model – is used to analyse and model time series when the error terms are assumed to have a characteristic variance.

General Algebraic Modelling System – is a high-level modelling system for mathematical programming and optimization that consists of a language compiler and a stable of integrated high-performance solvers.

Gate Closure - Deadline for the participation to a given market or mechanism by providing technical and commercial data regarding its schedule and prices to either the TSO or the Market Operator, as the case may be. For the Day Ahead market the gate closure is set to 12 p.m. (midday), as for the Intraday Market, gate closure is set to 60 minutes ahead of delivery.

Imbalance - Deviation between generation, consumption and commercial transactions (in all timeframes - commercial transactions include sales and purchases on organised markets or between BREs) of a BRE.

Intraday Market - Market timeframe beginning at 15 p.m. and as soon as a match between supply and demand is made, and ending at the intraday gate closure time, where commercial transactions are executed prior to the delivery of traded products.

Imbalance Settlement - A financial settlement mechanism aiming at charging or paying the BREs for their imbalances.

Load Factor – Ration between wind power production and the installed capacity of wind power generation.

Long Position - A producer is long whenever he as produced more electricity than what he has sold in the markets. The electrical system can also be long whenever production exceeds demand.

Pay-as-bid - Also known as discriminatory pricing is a model in which all suppliers of control power receive the price included in their individual bids when called to supply control power.

Primary Control Reserve - is a local automatic control system which delivers reserve power to counter frequency change. It constantly corrects frequency deviations (fluctuations) from the nominal value. They do so in order to maintain the power balance in the whole synchronously interconnected Transmission System. It is activated in less than 30 seconds and has a maximal power of 600 MW. Its participation is compulsory.

Replacement Reserves - consist in the TCR mentioned bellow but under the new ENTSO-E terminology.

Réseau de Transport d'Électricité – The Electricity Transmission Network is the electricity transmission system operator of France.

Variable Generation Producer - It is a producer that does not have full knowledge of the output of its production as it comes from a renewable source such as the wind or the sun, over which he does not have control.

Seasonal Autoregressive Integrated Moving Average – model used to analyse or predict future values of a time series that has a seasonal effect.

Secondary Control Reserve - is a centralised automatic control system that delivers reserve power in order to replace the need for PCR and bring interchange programs to their target values. It restores the frequency to the nominal value and power balance to the forecast value after a sudden system imbalance. It is activated in less than 15 minutes and its maximal power ranges from 500 MW to 1000 MW. It can also be activated manually.

Settlement - Involves the ex-post attribution of imbalances to different BREs. Once the attribution is done, the TSO invoices BREs for the net cost of its own imbalance.

Short Position - The opposite of Long Position: a producer will generate less power than what he have sold. The system has less production than demand.

System Control - The TSO is required to ensure system stability by controlling adequacy of power and ancillary services, voltage levels and frequency levels.

System Operation - System operation includes monitoring, data exchange, states of system operation, training, safety coordination, emergency procedures and investigation.

System Security - The ability of the power system to withstand unexpected disturbances or contingencies.

System Services - Are a set of Balancing Services secured by the TSO from the BSPs. PCR, SCR and Reactive Power Control are referee to as System Services and their cost is socialised and recovered by the grid tariffs (TURPE).

System Stability - System stability is defined by the acceptable operating boundaries of the Transmission System in terms of respecting of the constraints of Voltage Stability, Small Disturbance Angle Stability and Transient Stability.

Tertiary Control Reserve - is a manual change in the dispatching and unit commitment in order to restore the SCR, to manage possible congestions, and to bring back both the frequency and the interchange programs to their target if the SCR is not sufficient. It consists of the Fast Reserve, which can be activated in 13 minutes with a maximal power of 1000 MW; an additional 500 MW complementary reserve activated in 30 minutes and an average of 450 MW from consumers that can be activated in less than 2 hours only when required by the TSO. There are other reserves with variable maximal powers and activation times that can be provided by french BSPs or foreign ones. All these reserves participate in a pay-as-bid auction and the BSPs are free to name their prices (except for the ones that have a previous contract with the TSO).

Transmission System Operator - is the entity responsible for operating, ensuring the maintenance of and, when necessary, developing the transmission system in a given area and, where applicable, its interconnections with other systems, and for ensuring the long-term ability of the system to meet reasonable demands for the transmission of electricity, as defined in the IV Chapter of the European Directive 2009/72/EC. In order to accomplish its task the TSO makes use of the System Services and the Balancing Mechanism.

Bibliography

[1] EU, “Directive 2009/28/EC on the promotion of the use of energy fromrenewable sources”, Official Journal of the European Union, April 2009.

[2] RTE, “Bilan électrique 2013”, pp. 16, 2013.

[3] Zugno, M.; Morales, J.M.; Pinson, P.; Madsen, H., “Pool Strategy of a Price-Maker Wind Power Producer”, *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3440–3450, August 2013.

[4] Chaves-Ávila, J. P.; Hakvoort, R. A.; Ramos, A., “Short-term strategies for Dutch wind power producers to reduce imbalance costs”, *Energy Policy*, vol. 52, pp. 573–582, January 2013.

[5] Jónsson, T., “Forecasting of electricity prices accounting for wind power predictions”, Masters Thesis, IMM-DTU, Kongens Lyngby, 2008.

[6] Bessa, R.J., “Methodologies for the participation of an electric vehicles’ aggregator in the electricity market”, PhD Thesis, FEUP, Porto, 2013.

[7] Chaves-Ávila, J. P.; Hakvoort, R. A.; Ramos, A., “The impact of European balancing rules on wind power economics and on short-term bidding strategies”, *Energy Policy*, vol. 68, pp. 383–393, May 2014.

[8] Chaves-Ávila, J. P.; Hakvoort, R. A.; Ramos, A., “Impact of balancing rules on wind power economics in Belgium, Denmark, Germany and the Netherlands”, 2012, *Working Paper*.

[9] Bourry, F.; Juban, J.; Costa, L. M.; Kariniotakis, G., “Advanced strategies for wind power trading in short-term electricity markets”, *European Wind Energy Conference & Exhibition EWEC*, Brussels, April 2008.

[10] Botterud, A. et al., “Wind power trading under uncertainty in LMP markets”, *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 894–903, May 2012.

[11] Bourry, F.; Kariniotakis, G., “Strategies for wind power trading in sequential short-term electricity markets”, *European Wind Energy Conference & Exhibition EWEC*, Marseille, April 2009.

[12] Zugno, M.; Jónsson, T.; Pinson, P., "Trading wind energy on the basis of probabilistic forecasts both of wind generation and of market quantities", *Wind Energy*, vol. 16, no. 6, pp. 909–926, September 2013.

[13] Schertzer, J.-M., "Impact of Renewable Intermittent Generation on short-term Security Margins", Masters Thesis, Master REST & EDF R&D, Paris, September 2013.

[14] Giebel, G.; Brownsword, R.; Kariniotakis, G.; Denhard, M.; Draxl, C., "The State of the Art in Short-Term Prediction of Wind Power: A Literature Overview", 2nd Edition, ANEMO.plus, 2011.

[15] Weron, R., "A review of electricity price forecasting: The past, the present and the future", Wroclaw, HSC/14/02, 2014.

[16] CRE, "Echanges d'électricité aux frontières Utilization et gestion des interconexions en 2012", pp. 56, Jun. 2013.

[17] Barette, V., "Note introductive aux modèles factoriels et à leurs applications élémentaires en valorisation", EDF R&D, 2006, *Private Communication*.

[18] RTE, "Documentation Technique de Référence", c. 4, art. 4.1, 2014.

[19] Bessa, R. J.; Matos, M. A., "Forecasting Issues for Managing a Portfolio of Electric Vehicles under a Smart Grid Paradigm", *3rd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe),* pp. 1–8, October 2012.

[20] W. Li and R. Billinton, *Reliability Assessment of Electrical Power Systems Using Monte Carlo Methods*, c. 3, pp. 33-73, Plenum Press, New York , 1994.

[21] Matos, M. A., "Decision under risk as a multicriteria problem", *European Journal of Operational Research*, vol. 181, no. 3, pp. 1516–1529, September 2007.

[22] EPEX SPOT SE, http://www.epexspot.com/en/, 2014 (accessed 27 June 2014).

[23] RTE, http://clients.rte-france.com/lang/fr/visiteurs/vie/courbes_methodologie.jsp, 2012 (accessed 27 June 2014).